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

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Abstract

Governments often subsidize private R&D using both grants and tax incentives. This paper studies whether they are complements or substitutes. I take a difference-in-discontinuities approach to examine small firms in the United Kingdom and find that increasing tax credit generosity enhances the effect of grant funding on R&D, suggesting that they are complements. Financing constraints are likely at play. The effects are most substantial for firms that appear constrained, and by implementing another quasi-experimental research design, I find that the instruments are substitutes for larger firms, which are usually less constrained. Some alternative explanations can be ruled out.

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

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

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1 Introduction

Productivity growth has been declining in many developed countries since the 1970s (Bloom, Van Reenen and Williams 2019). Innovation will likely be at the heart of revitalizing these economies, as it is a central driver of growth and competitiveness, but it tends to be underprovided by markets due to knowledge spillovers (Nelson 1959; Arrow 1962). This market failure underpins justifications for intervention, and indeed, governments globally spend hundreds of billions of dollars on subsidies for research and development (R&D) every year. Yet understanding how to design such incentives so they live up to their promise is a longstanding and increasingly pressing challenge, especially as policymakers are revisiting their industrial strategies and support for R&D is playing a prominent role.[1]

Subsidies for private R&D most commonly come in the form of direct grants and fiscal incentives, and there is growing evidence that they both boost R&D investment and innovation. One important and unanswered question, though, is whether grants and tax credits interact in their effects on firm behavior, as firms frequently can tap into both. If so, this interaction could either enhance or dampen the marginal returns to each instrument depending on whether they are complements or substitutes.

Consider how grants may help firms overcome high upfront costs associated with starting a new project, like buying new equipment or setting up a lab. This might especially be the case if firms face financing constraints. They can typically then claim tax credits on additional R&D spending beyond what is funded by the grant, such as on the salaries of scientists and engineers. Increasing the generosity of tax credits could enhance the marginal return to grant funding if it enables firms to hire more R&D workers that put the machinery to use. This would suggest that the two support schemes are complements. On the other hand, firms might use the instruments interchangeably to subsidize expenditures that qualify for both, implying that they are substitutes.

In this paper, I present new evidence on whether direct grants and tax credits for R&D are complements or substitutes. Studying this question is empirically difficult because it

[1] For example, President Biden's budget request for FY2023 included $205 billion for total Federal R&D, an all-time high and 28% increase over FY2021, with $111 billion of this specifically for basic and applied research (The White House 2022). The UK's 2017 Industrial Strategy also set a target of increasing overall UK investment in R&D to 2.4% of GDP by 2027. (Vagnoni n.d.).

requires variation in both support schemes and randomization in industrial policy is rare. I overcome this by exploiting several sources of policy-induced variation in the cost of investing in R&D for firms in the United Kingdom and estimating the effects of subsidy interactions on their R&D expenditures. Small firms are particularly important in the innovation context because of how sensitivities to cost shocks and the types of innovations firms pursue tend to differ across the size distribution, but they are often difficult to study due to data limitations. To provide further insight into the importance of firm size heterogeneity, I also implement a second quasi-experimental research design to examine larger firms.

More specifically, I take a difference-in-discontinuities approach to study the interaction effects of grant funding from Innovate UK, the UK's largest public funding body for private sector innovation, and the UK's R&D Tax Relief for Corporation Tax Scheme (henceforth "tax credit"). I use a discontinuity in grant generosity rates (i.e., the proportion of project costs that is subsidized) to estimate the effect of grant funding on R&D, whereby firms under a size threshold set by Innovate UK at the time when the program launched benefit from a grant funding rate that is 15% higher, on average, than it is for firms over the threshold. To capture the interaction effect, I then test whether there is a difference in the discontinuity (i.e., a change in the grant effect) when tax credit rates increase.

The validity of this research design relies upon a few key conditions being met. Perhaps most importantly, firms must not strategically manipulate their size around the grant funding threshold and increases in tax credit rates must not induce such behavior. The density of firms around the cutoff appears smooth and there is no evidence of bunching in response to the tax credit rate changes. This also suggests that there are likely no other policies generating different incentives to invest in R&D at the cutoff, and through manual inspection, I do not find any that impose the same thresholds. Lastly, firms below and above the threshold appear to be similar in observable characteristics.

The results indicate that the two support schemes are complements for these small firms, as raising tax credit generosity enhances the effect of grant funding on R&D. In my preferred specification, the 33% increase in tax credit benefits augments the marginal effect of grant funding by about £430,000. The magnitude of this effect is relatively big when compared to the estimation sample's mean R&D expenditures of $£218,000$, but it is reasonable given the context, as the tax credit rate hike is higher than the difference in grant funding generosity. Furthermore, salaries for R&D workers often account for a significant portion of R&D expenditures, and tax credits primarily go towards such expenses. The findings are robust across various modelling assumptions and falsification tests.

To explore some of the potential mechanisms underlying these results, I conduct a series of additional empirical tests and conclude that they are likely driven by financial constraints. First, I find that the interaction effects are much stronger for firms that appear constrained according to three proxies: short-term debt, operating profit, and "available funds" for internally-financing projects. Second, I implement another quasi-experimental research design to study larger firms, which are less likely to be constrained. Finding that the complementarity also exists for these firms would suggest that financing constraints may not be a key driver. My approach for studying larger firms entails exploiting a discontinuity in the tax credit rate, whereby firms with fewer than 500 employees benefit from more generous tax credits. I estimate the effect of grant funding on each side of this threshold within a tight window around it and calculate the difference in the grant funding effects to capture the interaction.[2] The results indicate that more generous tax credits dampen the effect of grant funding, suggesting that they are substitutes for these larger firms.

I explore some alternative mechanisms as well. I do not find evidence that the results are driven by firms pursuing larger projects, for example, or by pivoting in the type of research that they propose in grant applications. I also explore whether the funding agency preferentially treats past grant winners, as this might suggest that the experience reduced information asymmetries, or that they are selecting projects that they view as having a higher likelihood of success because of already receiving funding. I do not find evidence that this occurs.

This paper is the first, to my knowledge, to provide empirical evidence of whether R&D grants and tax credits are complements or substitutes. Research in the innovation literature has found that they both have positive effects on private sector innovative activity when studying them separately. For example, Bloom, Griffith and Van Reenen (2002), Rao (2016),

[2] Dechezleprêtre, Einiö, Martin, Nguyen and Van Reenen (2019) and Guceri and Liu (2019) also use the firm size thresholds when studying the UK's tax credit policy on its own.

Guceri and Liu (2019), Dechezleprêtre et al. (2019), and Agrawal, Rosell and Simcoe (2020) find that tax incentives increase R&D, and Bronzini and Iachini (2014), Howell (2017), and Azoulay, Graff Zivin, Li and Sampat (2018) find that direct grants have positive effects on patenting. As firms frequently use both, the interactions of these two instruments could also impact their returns, so developing a better understanding of this relationship is important for policy design. My results help narrow this knowledge gap.

Understanding subsidy interactions specifically for small firms also provides new insight into the implications of innovation policy, as they tend to contribute disproportionately to major innovations and grow faster than larger firms but they are often difficult to study due to data limitations (Akcigit and Kerr 2018). One notable exception is Agrawal et al. (2020)'s study of how R&D tax credits impact small firms' R&D in Canada.

The findings are also timely for policy amid the productivity slowdown that many countries have experienced over the past several decades. Providing incentives for firms to invest in R&D has been at the forefront of the industrial strategies that many nations are currently revisiting. Direct grants and tax credits are two of the most commonly deployed approaches, and my results shed light on the importance of considering the policy mix when designing such incentives. Furthermore, while others have shown that grants can alleviate financing constraints, my findings suggest that tax credits can also play a role by enhancing the effectiveness of grant funding.

Lastly, policy interactions are common in many economic settings, but there is limited, well-identified evidence of their effects. This paper therefore also may be of interest to other fields for which policy interactions are prevalent, especially since firm size is frequently used to determine how policies are applied.[3]

The remainder of this paper is organized as follows. Section 2 provides background on how governments often subsidize private R&D and the specific programs that I study. Section 3 discusses my empirical approach and data, and I present the main findings in Section 4. Section 5 explores the underlying mechanisms and I conclude in Section 6.

[3]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).

2 Background and Institutional Details

In this section, I discuss the ways in which governments often fund private R&D, provide intuition around how grants and tax credits could be complements or substitutes, and describe the institutional details of the specific programs that I study.

2.1 Public Funding for Private R&D

Government financial support schemes promoting private R&D take on different forms, with direct grants and tax incentives being the most common. Grants are typically awarded through a competitive process whereby firms submit proposals for specific projects that they wish to pursue and funding agencies select which ones to fund. Such direct subsidy programs often provide the agency with the opportunity to target certain industries, projects, or types of R&D. On the other hand, any firm investing in R&D can typically benefit from fiscal incentives. Their design varies across countries—for example, the U.S. tax credit is based on incremental increases in R&D whereas the U.K.'s is volume-based—but in general, they allow for a more generous deduction against corporate tax liabilities beyond the standard write-off that applies to other current costs. While direct grants are usually provided to firms upfront, tax credits are claimed after expenditures are incurred.

Overall, public spending supporting business R&D in many countries is increasing, and policymakers adopt a range of mixes between the two types of subsidies.[4] Fiscal incentives in particular have been growing in popularity over the past few decades. Tax credits account for more of the support in the UK as a percentage of GDP relative to direct grants as well as in many European countries, which I illustrate in Figure 1. In the UK, total government support for private R&D increased from about 0.10% of GDP to 0.37% between 2000 and 2018, with fiscal incentive support specifically increasing from 0.01% of GDP to 0.29%. The UK was second among all OECD countries by 2019 in terms of total government support as a percentage of GDP.

[FIGURE 1 HERE]

[4] All figures discussed in this section are according to data from the OECD's Main Science and Technology Indicators database.

A similar trend in the share of public support coming from tax incentives can be seen across the EU-27 and in OECD countries in aggregate but with less growth in total subsidy funding as a percentage of GDP. The number of countries providing R&D tax relief in the OECD increased from 20 in 2000 to 34 in 2021, and many have been increasing the generosity of tax credit rates over time as well (OECD 2020).

On the other hand, the U.S. has historically relied much more upon direct grants, and although R&D financed by both subsidy types in total as a percentage of GDP was still above the OECD average as of 2021, it has declined since its peak in 2008-09 when a surge of funding was allocated through the American Recovery and Reinvestment Act of 2009 in response to the great recession. Subsidies in total increased from 0.24% of GDP in 2000 to 0.33% in 2009 and then were back down to 0.24% in 2018. The majority of funding in this time period came from grants, but the share coming in the form of tax credits has started to increase in more recent years such that they were split about evenly in 2018. That said, the generosity of the tax credit declined slightly, falling to just 0.07 for SMEs whereas the OECD median rate was 0.20.

2.2 Grants and Tax Credits as Complements or Substitutes

Direct subsidies and tax credits reduce the cost of investing in R&D and thus should, in theory, increase R&D expenditures under standard assumptions. However, as firms frequently are able to access both, the subsidies may interact in their effects on firm behavior. If this is the case, the marginal effect of one subsidy type is not just its direct effect but the sum of the direct effect and the indirect effect through the other (i.e., the cross-partial). In other words, the interaction between the two could enhance or dampen the returns to each depending on whether they are complements or substitutes.

There are various ways in which such interactions could emerge that make the direction of this relationship theoretically ambiguous. As one example, consider a world in which some firms face financing constraints. They are innovative but small and do not have sufficient internal resources to begin developing a new technology, and they have not yet established a track record of success, so they struggle to secure external finance due to information asymmetries. Winning a grant that provides upfront funding allows them to overcome such constraints and purchase new machinery or set up a lab. Additional R&D expenditures beyond that which is funded by the grant—such as for the salaries of scientists and engineers—qualify for tax credits. When tax credits become more generous (i.e., the proportion of spending that is refunded), they can hire more labor to put the grant-funded capital to use. The tax credits thus enhance the marginal effect of grant funding on total R&D expenditures in this scenario, suggesting that the two instruments are complements.

On the other hand, consider firms that do not face such financing constraints and therefore do not require upfront funding to start a new project. These firms may still apply for and receive grants but use the two support schemes interchangeably for expenditures that qualify for both (like labor). In this case, an increase in the tax credit rate might reduce the demand for grant funding, suggesting that they are substitutes.

Understanding whether direct grants and tax credits are complements or substitutes entails knowing whether firm costs are super- or sub-modular in the two subsidy types. As such, one way to explore whether they are complements or substitutes is to estimate their interaction effects. This is the empirical approach that I take, observing how the marginal effect of grant funding changes with increases in tax credit generosity. Interpreting the results does not rely on a specific theory. Instead, after presenting my main findings, I provide additional sets of results to shed light on some potential explanations.

2.3 Institutional Details

2.3.1 Direct Grants from Innovate UK

Innovate UK, a non-departmental public body, is the UK's premier grant-awarding agency for the private sector, providing more than £2 billion in direct funding for R&D to private businesses since 2007 that are awarded through competitions (InnovateUK n.d.). The competitions are often sector-specific or mission-driven but they can also be open, calling for any novel R&D innovations that have potential to make a "significant impact on the UK economy." Applicants submit proposals that detail the scope of the project, including costs, timelines, and planned activities. Once selected, awardees are subjected to finance checks for the duration of the funded project. All costs must be incurred and paid between the proposal's start and end dates, and claims are subject to independent audits.

The main feature of the program that I exploit is a funding rule that determines grant "rates" (i.e., the proportion of the proposed project costs that is funded by the grant). The Innovate UK guidelines define different funding rates for firms of different sizes, which were set at the program's launch. Firms are classified as small, medium, or large based upon staff headcount and either turnover or balance sheet totals following the definitions set out by the European Commission. Small firms are classified as those with fewer than 50 employees and either a maximum turnover or balance sheet total of €10m. While the UK has a number of other support programs for private businesses in place for small- and medium-sized enterprises (SMEs), far fewer specifically target small firms as defined in the same way. Other policies targeting small firms generally set different eligibility requirements and thresholds, which I discuss in more detail in Section 3.3.

Firms under the small firm threshold 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, those just over the threshold are eligible for funding that subsidizes 60 percent, 60 percent, and 35 percent of project costs, respectively. Fundamental research projects are 100 percent funded for firms of all sizes. This averages to the grant funding rates for firms just under the threshold being 15%, or 7.5 percentage points, higher than they are for those over it.

2.3.2 R&D Tax Credits in the UK

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: more than £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) and it accounted for more than 80% of government support for business R&D in 2019.

The program design is volume-based, reducing corporate tax liabilities through an enhanced deduction of current R&D expenditures from taxable income. This differs from incremental R&D tax incentives used in some other countries, such as in the U.S, where firms benefit only if their R&D expenditures exceed some base level of previous expenditures. The main benefit that the volume-based design offers is simplicity, and thus it is widely used by firms investing in R&D despite their size or age. Furthermore, loss-making firms also benefit through a payable tax credit. The enhancement rates are particularly generous for SMEs, and increasingly so over time. Table 1 details all of the components that determine a firm's tax credit rate from 2008 forward. For profit-making firms, the percentage of R&D expenditures that the tax credit subsidizes is equal to the product of the enhancement rate and the corporate tax rate.[5] The same formula applies for loss-making firms except that the corporate tax rate is replaced with the payable credit rate.

[TABLE 1 HERE]

Between 2008 and 2017, the enhancement rate increased from 0.75 to 1.30. I exploit changes over time in my empirical analyses. The first major increase happened in 2011, followed by another big increase in 2012 and smaller changes in later years. I split the years into a pre-tax credit change period (2008-2012) and post-tax credit rate change period (2013-2017) for the empirical analyses and use the average tax credit benefit in the two periods (i.e., the percentage of R&D expenditures that is subsidized according to the formula described above).[6] The average benefit increased by 33% from 16.5% of expenditures in the pre-tax credit change period to 22% afterwards.

Another feature of the policy is that, as of 2008, the firm size thresholds that determines SME status under the R&D tax credit scheme doubled to include firms with fewer than 500 employees and either no more than €100m in sales or no more than €86m in total assets. This new SME definition applied for R&D tax credit eligibility purposes only and the original lower thresholds remained in place for all other policies in the UK. I do not use this policy change or the SME thresholds throughout the main analysis when studying small firms but do when exploring firm size heterogeneity to study larger firms. Despite these firms being labeled as SMEs for the R&D tax credit purposes, I refer to firms with more

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

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

than 250 employees as being large because they are considered as such for all other intents and purposes in the UK, and I specifically study those around the 500 employee threshold in my empirical analyses.[7]

Appendix Table C.1 provides the enhancement rates for firms that are over the R&D tax credit SME thresholds from 2008 to 2014. On average, the proportion of R&D that is subsidized for firms over the thresholds is 17 percentage points lower than it is for those under them. On average, the proportion of R&D that is subsidized for firms over the thresholds is 17 percentage points lower than it is for those under them.

3 Empirical Strategy and Data

This section starts by describes my empirical strategy and data. I then discuss the identification assumptions and explore the research design's validity.

3.1 Econometric Framework

To study whether grant funding and tax credits are complements or substitutes, I estimate the effects of their interactions on R&D by using the two main sources of policy-induced variation in the cost of investing in R&D described in Section 2: 1) the discontinuity in Innovate UK's grant funding rates, whereby firms with fewer than 50 employees are eligible for a larger proportion of their project to be subsidized, and 2) before and after variation associated with when the tax credit rate increases, using the average tax credit benefit in 2008-2012 as the pre-policy period and 2013-2017 as the post-policy period.

I implement a difference-in-discontinuities ("diff-in-disc") research design. Intuitively, the approach entails testing whether increases in tax credit rates affect any discontinuity in R&D expenditures that might exist at the grant funding threshold.[8] I estimate a local linear regression of the following form:

[7] Dechezleprêtre et al. (2019) use these thresholds to study the effects of the tax credit policy on its own, showing that the more generous rates have positive effects on R&D expenditures and patenting. I use them when examining the tax credit interaction with grant funding.

[8] Grembi, Nannicini and Troiano (2016) show how the diff-in-disc estimator identifies the (local) average treatment effect of an interaction like this.

$$
\begin{aligned}
Y_{it} = \delta_0 + \delta_1 A^*_{it} + J_{it}(\gamma_0 + \gamma_1 A^*_{it}) + T_t[\alpha_0 + \alpha_1 A^*_{it} + J_{it}(\beta_0 + \beta_1 A^*_{it})] \\
+ \mathbf{X}_{it}\phi + \gamma_i + \delta_{ts} + \varepsilon_{it},
\end{aligned} \tag{1}
$$

where Y_{it} is the outcome variable for firm i (primarily R&D expenditures), J_{it} is an indicator for grant rate treatment status equal to 1 if firm i's (lagged) employment is less than 50 when receiving a grant and zero otherwise, T_t is an indicator equal to 1 in the tax credit rate increase post-tax credit rate increase period and zero in the pre-policy change period, and ε_{it} is the random error.[9] The (lagged) employment function, $A^*_{it} = A_{it} - A_c$, is normalized at the cutoff point of the running variable, A_c, and its slope is allowed to differ on each side of the cutoff following the standard for regression discontinuity designs (RDDs). I use employment as the running variable since it is the binding eligibility criteria, however firms also must have no more than €10m in turnover or total assets. I account for this by limiting the estimation sample to include only those with lagged turnover or total assets under those thresholds.

The main coefficient of interest is β_0, the diff-in-disc estimator, identifying the subsidy interaction effect. If β_0 is positive, increasing tax credit generosity enhances the effect of grant funding, suggesting that the two subsidies are complements. Alternatively, if β_0 is negative, they are substitutes. Finding no interaction effect would imply that they are independent.

Consistent with how a standard RDD approach would be carried out, I estimate this model for firms just around the 50 employee cutoff point using varying sample windows, restricting the data to $A_{it} \in [A_c - h, A_c + h]$, where h represents a distance from the threshold. Throughout the analysis, I include observations for the year in which the firm receives a grant as well as the two years that follow. I therefore define firms as being treated (i.e., as falling below the threshold and qualifying for more generous grant funding rates) for all three years if the firm qualifies in the year before it wins the grant.[10]

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

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

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

3.2 Data and Descriptive Statistics

I compile data from two sources for the main analysis. First, I collect grant-level information from Innovate UK's public Transparency Database for 2005 through 2017. This data provides basic information on all grants distributed by the program, such as when organizations received them, the funding amount, and total proposed project costs. It also includes company registration numbers (CRNs) so that firms can be uniquely identified and matched to other firm-level data sets.

For information on R&D expenditures, the main outcome variable that I study, as well as firm size and other financial variables used throughout the analysis, I match the grant data to Bureau van Dijk's Financial Analysis Made Easy (FAME) database. This is a commercial database containing detailed balance sheet data on about 11 million companies and unincorporated businesses in the UK and Ireland. Official filings content are gathered from Companies House and then enriched with additional efforts to ensure accuracy.

Of the 10,787 firm-year observations in the Innovate UK data, only 353 do not have matches in FAME (a 97% match rate), resulting in 10,434 observations across 6,479 unique firms. Appendix A details the steps I then take to prepare the data, such as dropping observations with clear data entry errors as well as the top one percent of the R&D investment distribution to help ensure the findings are not driven by outliers, as firm-level innovation investments can be highly volatile (Bronzini and Iachini 2014). I also assume that missing R&D expenditures represent zeros, which I address in more detail in Section 4.3. Finally, I limit the sample to 2008-2017, as a much smaller number of grants were provided in the first few years after the program's launch, and I keep observations for the year in which a firm

eligibility status. I also use employment from the year prior to receiving a grant when constructing the running variables.

receives a grant as well as the two years that follow.

Table 2 presents summary statistics of the final prepared data.[11] The full data set before limiting the sample to small firms includes 10,029 grants across 6,340 unique firms, and for firms with 20 to 80 employees, which is the baseline sub-sample that I use throughout the analysis, there are 721 grants given to 533 unique firms. Annual R&D expenditures are about £179,000 on average.

[TABLE 2 HERE]

3.3 Identification and Research Design Validity

The conditions for a difference-in-discontinuities approach to be valid are similar to those of a standard RDD but with additional elements related to the time variation dimension. First, the running variable must be determined before treatment is assigned. This is the case in my setting because of the firm's size in the year in which it applies for the grant determines treatment (i.e., the higher grant rate), which comes before the time at which it actually receives the grant.

A related condition is that the running variable—number of employees—cannot be manipulated around the cutoff that determines the grant funding generosity rate. Such manipulation of firm size would be problematic because it would imply that firms below and above the threshold differ in systematic ways that are unobservable and correlated with R&D activities. The typical approach to exploring this is to examine whether there is bunching around the cutoff. The diff-in-disc design also requires there to not be a *change* in the density of firms around the cutoff before and after the tax credit rate increases.

To explore this, I start by examining whether there is a difference in the density of firms at the 50 employee threshold on average across all years. I plot the distribution of firms by size as a histogram and a scatter plot using a third-order polynomial fit in Panels A and B of Appendix Figure B.1, respectively. There does not appear to be bunching visually, and the formal McCrary density test also does not provide evidence of manipulation[12]

[11] All nominal financial variables are converted to 2010 real prices using the World Bank's Consumer Price Index for the UK.

[12] The log difference in the density height is 0.121 with a standard error of 0.163, which is not statistically significant.

Next, to observe whether the increase in tax credit rates induced manipulation, I carry out the same exercises separately for the pre-tax credit change years (Panels A and B of Figure 2) and post-tax credit change years (Panels C and D of Figure 2) and test whether there is a change in any such discontinuity. Firms do not appear to manipulate their size in either period and visual inspection suggests that there is no change in the density around the threshold. The formal tests also do not provide evidence of bunching or a change in bunching. The differences at the threshold are statistically zero and the difference-in-discontinuity is as well. A simple t-test for whether the difference is statistically significant produces a t-statistic of 1.123.[13]

[FIGURE 2 HERE]

The third assumption is that the cutoff is not endogenously determined by firm characteristics. A standard way of testing this is to examine whether observable covariates are continuous across the threshold. In the difference-in-discontinuities setting, the change in tax credit rates also should not induce differences in covariates for firms around the cutoff. I estimate a standard RDD model as well as the diff-in-disc specification of Equation 1 using age and operating cash in the year before they win a grant as the outcome variables and do not find evidence of any such discontinuity or differences in discontinuities (see Columns 1-4 of Appendix Table C.2).

I also explore whether firms under and over the threshold are just as likely to win a grant. Since grant generosity rates differ, firms may have different propensities to apply, which could affect competition as well as the likelihood of winning and thus lead to differences in the quality of projects. Likewise, increases in tax credit rates might induce such behavior if, for example, the more generous support for additional expenditures makes applying for a grant more attractive for firms on one side of the threshold more so than the other.

It is worth noting that covariates would likely differ at the threshold if this is the case. However, the ideal approach to testing it directly would be to see if there are differences in the number of applications and applicants' characteristics. Unfortunately I have not been able to access data on all applicants. Alternatively, I can provide some insight into

[13] The log difference is 0.491 with a standard error of 0.283 in the 2008-12 period and -0.112 with a standard error of 0.184 in the post period.

differences in the likelihood of winning a grant for firms that win one at some point in time. My sample includes observations for the years in which firms receive grants as well as the two years that follow, and these firms do not win grants every year. I estimate the effects using an indicator equal to one if the firm receives a grant that year and zero otherwise as the dependent variable and provide the results in Columns 5-6 of Appendix Table C.2. The likelihood of receiving a grant is smooth across the threshold and there is also no evidence of tax credits inducing differences.

Another way in which the cutoff independence assumption might be violated is if the funding agency preferentially treats certain firm size groups. Results from the preceding test for whether firms under the threshold are more likely to receive a grant suggests that this is probably not the case (see Columns 5-6 of Appendix Table C.2). The other balance tests also suggest that the threshold is independent from their evaluation process, as preferential treatment would likely lead to differences in firm characteristics—for example, perhaps weaker firms end up receiving funding if the agency aims to disproportionately fund small firms. Another point to highlight, though, is that Innovate UK more frequently limits eligibility to SMEs rather than strictly small firms when they do indeed target smaller firms, so it is more common for the applicant pools to include firms on both sides of the small firm threshold.

Lastly, the final assumption is that there are no other policies generating different incentives to invest in R&D for firms just under and over the small firm size threshold, and likewise, no changes in such policies aligning with the tax credit rate increases if they do exist. The lack of firm size manipulation is consistent with this being true, as confounding policies would likely induce the same type of sorting.

I dig into this further, though, since there are policies like this in other countries.[14] I manually reviewed many UK programs and policies that provide incentives based on firm size (see Appendix Table C.3). The majority of policies with preferential treatment tend to include both small- and medium-sized enterprises, which are defined as those with fewer than 250 employees. Those that do target small firms also tend to define "small" based on various other criteria and thresholds. One thing to note though is that financial reporting

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

requirements differ for small firms. This should not generate different incentives to invest in R&D, but I explore the implications of this further in Section 4.3.

4 Main Results

4.1 Graphical Evidence

I now turn to the main results and start with a visual depiction in Figure 3. Limiting the sample to firms with 20 to 80 employees in the year before they receive a grant, I create bins of observations across the firm size distribution and plot their average R&D expenditures separately for the years before the tax credit rate increased (Panel A) and after (Panel B).[15] There is no clear discontinuity in R&D expenditures at the threshold when tax credits are lower (2008-2012), but R&D expenditures for firms just under the threshold jump substantially once tax credit rates increase. Firms over the small firm threshold also increase R&D effort as tax credits also increase for them but to a lesser degree, and a clear discontinuity emerges relative to the pre-tax credit change period.

[FIGURE 3 HERE]

This jump in R&D expenditures at the threshold corresponds with the difference-in-discontinuity estimate, β_0 of Equation 1, and direction of the jump is consistent with the two subsidies being complements.

4.2 Econometric Results

Moving on to the econometric analysis, I estimate the subsidy interaction effect on R&D spending using the model of Equation 1 and present the results in Table 3. The primary coefficient of interest is the diff-in-disc estimate in the first row, capturing the impact of increasing tax credit rates on the effect of grant funding. In Column 1, only firm fixed effects are included, and I add year fixed effects in Column 2, year-by-industry fixed effects in Column 3, and additional controls (total assets and current liabilities) in Column 4.

[15] I use quantile-spaced bins and assign weights based on their distance from the threshold.

The results are consistent with Figure 3. The interaction effect is positive and statistically significant, suggesting that grants and tax credits are complements for these firms, and the magnitude of the coefficient is stable when moving from Column 1 to 4. Taking Column 4 with all fixed effects and controls as the baseline specification, the results indicate that the increase in tax credit rates enhances the marginal effect of grant funding on R&D by about £430,000 on average.

[TABLE 3 HERE]

This effect is large relative to the mean value of R&D expenditures for firms in the estimation sample (£218,000). However, it is not unreasonably large when considering the size of the tax credit rate increase and the types of expenditures that it typically subsidizes (e.g., labor). The tax credit benefit increased from 24% increase in the tax credit rate for profit-making firms and 53% for loss-making firms, averaging to a 33% increase relative to the average 15% difference in grant funding rates.

4.3 Robustness Checks

4.3.1 No Evidence of Relabelling

One potential concern with interpreting these findings is that firms have an incentive to relabel other investments or expenditures as R&D when the generosity of the support schemes increases in order to reap larger rewards, which would imply that firms are not actually engaging in additional innovation activities (Hall and Van Reenen 2000; Agrawal et al. 2020). For example, Chen, Liu, Suarez Serrato and Yi Xu (2021) found that firms relabeled in response to a change in corporate tax rules in China. This is particularly a possibility for increases in the tax credit rate in my context, as expenditures are not monitored as closely as they are for grant-supported projects.

To explore this, I estimate the baseline model with ordinary investment as the dependent variable. Ordinary investment should decrease in response to the subsidies if firms are relabeling. I construct investment as the change in tangible assets relative to the preceding year plus depreciation following Zetlin-Jones and Shourideh (2017) as well as a second measure that omits depreciation to strictly capture changes in capital from year to year. The results are presented in Appendix Table C.4 using the investment variables in levels in Columns 1 and 2, and in Columns 3 and 4, I take the inverse hyperbolic sine. There are no statistically significant effects in all four cases and the coefficient signs are positive.

4.3.2 Financial Reporting Requirements and Missing Data

Although there are no confounding policies creating different incentives for firms to invest in R&D to the best of my knowledge, there are differences in financial reporting requirements. Small firms are only required to report a subset of information to Companies House, and R&D expenditures are not required. My assumption that missing R&D expenditures are zeros could therefore introduce some bias. For example, the interaction effects could be over-estimated if increases in the tax credit rate induce small firms to begin reporting, perhaps because reporting could reduce information asymmetries and increase access to capital. Observed changes in R&D for small firms due to tax credit rate increases might then be greater than the true effect if their expenditures are incorrectly assumed to be zero in the pre-tax credit change period.

To explore this, I estimate the effects on the likelihood of reporting other financial variables that small firms are also not required to report—profits, shareholder funds, and cost of sales. I consider missing data as truly not reported as opposed to zeros since these variables are much less likely to ever be zero, and I estimate the baseline model with an indicator equal to one if the variable is reported and zero otherwise as the dependent variable. Assuming that firms are more likely to report R&D if they also report this information, effects on the likelihood of reporting R&D likely follow similar patterns.

Appendix Table C.5 provides the results. I first estimate just the effect of grant funding conditional on the standard running variables and baseline controls in Columns 1-3 and then the full diff-in-disc model in Columns 4-6. There is no evidence of differences or changes in the likelihood of reporting.

4.3.3 Additional Robustness Checks

I carry out a number of final robustness checks to see if the baseline estimates are sensitive to my modelling choices and provide the results in C.6. I start by increasing the range of firm sizes included in the sample. Columns 1 and 2 show the effects when widening the window around the threshold to 10 to 90 and 1 to 100 employees, respectively. The magnitudes of the effects decrease slightly as the sub-sample increases, but they are stable in terms of their percentage increases over the sample means and statistically significant at the 1% and 5% levels. Next, Columns 3 and 4 provide results from increasing the running variable flexibility to include quadratic and cubic polynomials. The results hold here as well.

Lastly, to investigate whether effects at the small firm threshold arise by chance, I perform falsification tests by imposing pseudo-thresholds (30 and 70 employees) and estimating the diff-in-disc with these arbitrary cutoffs. Expenditures should be smooth across these thresholds since there are no differences in the cost of investing in R&D, and if they are not, this would suggest that the main results are simply an artifact of the data. The results in Columns 5 and 6 of Appendix Table C.6 show that there are indeed no effects.

5 What Drives Subsidy Complementarity?

In this section, I explore the potential mechanisms underlying the main findings, concluding that they most likely can be explained by firms facing financing constraints.

5.1 Unlikely Explanations

5.1.1 Increase in Grant Award Amounts

One explanation for the grant effect increasing is that firms under the grant threshold may propose higher project costs when the tax credit rates increase and thus receive bigger grant awards, either because they actually pursue more ambitious projects or because they manipulate the costs. For example, since tax credits help subsidize additional R&D spending, the more generous tax credits may enable them to invest in larger projects. To explore this, I estimate the subsidy interaction effect on proposed project costs, and I do not find evidence that this occurred (see Column 1 of Table 4.[16] I also interact the proposed project cost with the main diff-in-disc variable to see whether larger grants enhance the interaction effect further, but this does not appear to be the case (Column 2).

[TABLE 4 HERE]

5.1.2 Shift in Type of Research

The complementary also might emerge if firms pursue different *types* of research when tax credits become more generous, as the type of research determines the proportion of a project that is funded by the grant. This could be the case if tax credits are more important for the success of certain types of research, for instance. If one type of research requires more labor in addition to what is funded by the grant, or will in the future, the firm might pivot to focus on a different project, since R&D labor expenditures qualify for tax credits and can be substantial over a project's (or follow on project's) lifetime. This pivot may lead to grants having a bigger impact on a firm's total R&D expenditures.

I investigate this by estimating the subsidy effects on indicators for whether the project is a feasibility study (Column 3 of Table 4) or for developing a new prototype (Column 4 of Table 4).[17] There are no statistically significant effects.

5.1.3 Cumulative Grant Funding

Lastly, the effect of grants may increase over time if firms that previously won grants are more likely to win again.[18] For example, perhaps the funding agency favors past winners because it believes that a previously-funded project is more likely to succeed with continued support, as the agency has incentives to demonstrate program success in order to secure support from the government moving forward. Receiving a grant in the past also can provide signals that

[16]Since I define firms as treated by the grant for the year that they receive them as well as the following two years, I divide the grant amount by three and assign that amount as the dependent variable for each year that they are treated.

[17]The data do not provide an explicit category for whether the project is considered basic research, applied, or experimental, but it does break down project types in some ways, which I use as a proxy.

[18]Of course, for this to explain the results, there must be a difference in this behavior for firms just under or over the threshold that changes at the same time that the tax credit rates increased.

reduce information asymmetries that then increase the firm's chance of winning again.[19] I estimate the effect of the subsidies on the probability of winning a grant conditional on receiving a grant in the past and do not find evidence of this happening (Column 5 of Table 4).[20] I then also interact firms' cumulative awards with the main diff-in-disc variable (while also controlling for cumulative awards) and do not find that receiving funding in the past impacts the subsidy interaction effect (Column 6 of Table 4).

5.2 Financing Constraints as a Likely Explanation

Small firms may face financing constraints for a variety of reasons. Investors having insufficient knowledge about a firm's ability to develop a new technology could reduce its chances of securing external finance, for example. Such information asymmetries also could increase the cost of capital when such financing is secured. In this section, I provide two sets of results that are consistent with financing constraints being a driver of subsidy comlementarity.

5.2.1 Effects are Largest for Constrained Firms

Since constrained firms are more sensitive to cash flow shocks, the subsidy interaction effects should be larger for them. I estimate the effects separately for firms that appear to be more or less constrained according to three balance sheet items to explore this: short-term debt, operating profit, and "available funds." Firms facing financing constraints are more likely to have short-term loans and overdrafts, as these types of loans are typically sought when firms do not have internal funds to cover unexpected costs. Firms are also more likely to be able to internally-finance projects when their operating profits are healthier. As a final method for capturing this concept, I construct an "available funds" variable as the sum of before-tax profits and depreciation, capturing the internal resources available for investment.[21]

I split the baseline sample according to the median values of these financing constraint proxies in the year before firms receive grants and present the results in Table 5. The

[19] For example, once the funding agency has a few years to closely monitor a firm, it may be convinced that a project is likely to succeed.

[20] As before, since I do not have data for all applicants, my sample includes firms that win at some point in time and so non-receiving years are the two that follow any year in which it received a grant.

[21] I follow Zetlin-Jones and Shourideh (2017) in my approach.

effects on firms that appear "constrained" according to these measures are in odd-numbered columns and those that are "unconstrained" are in even-numbered columns. The effects are positive and statistically significant only for constrained firms, which is consistent with financing constraints being one of the underlying drivers of the main results.

[TABLE 5 HERE]

5.2.2 No Complementarity for Larger Firms

I now extend the analysis to study larger firms. Since larger firms are less likely to be constrained, I expect there to be no subsidy complementarity for these firms if financing constraints are indeed a key driver of the results. I implement a second quasi-experimental research design, as the approach for studying small firms entails limiting the sample to only firms within a narrow window around the small firm size threshold, and I find no evidence of subsidies being complements for these larger firms. They appear to be substitutes.

Data for Studying Larger Firms. Since the Innovate UK grant scheme primarily focuses on small and medium-sized firms, I must use a different measure of grant funding to study larger firms. I collect data from the UK's Business Enterprise Research and Development (BERD) database and Business Structure Database (BSD), which are provided by the Office of National Statistics (ONS). The BERD survey provides information on R&D expenditures for firms that are identified as actively performing R&D.

Although firm size is reported in the BERD, it is measured at the reporting unit level whereas tax credit rates are determined at the enterprise group level, so I gather employment data from the BSD, which covers this information for the universe of UK firms.[22] This allows me to determine tax credit rate eligibility by aggregating the data to the enterprise group level. I match firms over time to create unbalanced panels from 2009 through 2014.[23] The final dataset consists of about 2,000 to 2,500 enterprise groups per year. A full discussion of

[22]These data are derived from the Inter-Departmental Business Registrar (IDBR), which is a live register of administrative data collected by HMRC.The BSD includes all businesses that are liable for VAT and/or have at least one member of staff registered for the Pay as You Earn tax collection system.

[23]I start the sample in 2009 because the new size thresholds in the R&D tax credit policy that I use in my empirical approach were not implemented until 2008, so 2009 was the first year in which firms with up to 500 employees were eligible for the higher rates.

the data sources, preparation, and matching procedures can be found in Appendix A.[24]

The R&D expenditures measure in BERD is broken down by source of financing (i.e., the government, internal finance, and external private finance). I proxy for "direct grants" with the amount that is funded by the central government. These can include grants allocated through funding competitions, but also other forms of direct support.[25] Appendix Table C.7 provides summary statistics of the final data set. One observation to highlight is that they make, unsurprisingly, much larger R&D investments than small firms. Firms with 250 to 750 employees spend about £1.4 million on R&D on average.

A Discontinuity-in-Effects Research Design for Larger Firms. The key feature of the tax credit policy that I exploit now is a discontinuity in the tax credit rate, whereby firms with fewer than 500 employees benefit from higher tax credit rates than those above it.[26] This generates an exogenous difference in the cost of investing in R&D that does not align with how firm sizes are categorized in other policies.[27] Appendix Table C.1 details the enhancement rates and the associated tax credit benefits for which large firms were eligible over this time period.[28] On average, the benefit for firms just under the threshold is 17 percentage points higher than for those just over it.

While Dechezleprêtre et al. (2019) and Guceri and Liu (2019) use the policy's thresholds to identify the tax credit effect alone, I use it in a slightly different way to estimate the subsidy interaction effect. I limit the sample to a narrow window around the threshold, as one would do in a standard RDD, and estimate the effect of grant funding on R&D for firms just below and above the tax credit threshold separately. The difference in the grant effects at the cutoff captures whether more generous tax credits dampen or enhance the marginal effect of grants.

[24] The appendix also explains why these data are not preferred for the main small firm analysis, which is primarily because the coverage of small firms is not comprehensive and inconsistent methods for interpolation are used over time.

[25] The exact source is not identified, but importantly, the variable does not include funding received through R&D tax credits.

[26] Dechezleprêtre et al. (2019) and Guceri and Liu (2019) refer to these firms as SMEs, since they are defined as such for the R&D tax credit purposes. I refer to them as larger firms here because they are large firms by all other definitions in the UK and EU.

[27] SMEs are defined as those with fewer than 250 employees in all other contexts.

[28] Recall that the benefit as a percentage of R&D is a function of the corporate tax and enhancement rates.

As such, I estimate the following model:

$$Y_{it} = \alpha + \beta_1 G_{it} + \mathbf{X}_{it}\phi + \gamma_t + \delta_b + \eta_p + \varepsilon_{it}, \tag{2}$$

where Y_{it}, is R&D expenditures for firm i in year t and G_{it} is firm i's direct subsidy funding received (£000s) in year t. The running variable (number of employees) is allowed to differ on each side of the threshold and is included in matrix $\mathbf{X}_{it}$.[29] The specification also controls for macroeconomic shocks with year fixed effects (γ_t) as well as time-invariant mean differences in R&D effort across types of organizations with business structure fixed effects (δ_b) and product group fixed effects (η_p). Additional controls are included in $\mathbf{X}_{it}$: firm age, driving distance to the UK's primary funding agency HQ, and the total value of subsidies allocated in each industry-year. Standard errors are clustered by industry, defined as the first two digits of the firm's SIC.

The main coefficient of interest is β_1, which is the effect of total direct subsidy funding on R&D expenditures. I use a simple Z-score to test whether the difference in grant effects at the threshold is statistically significant. If the effect of grant funding for firms just below the threshold is higher than the effect for those just above it, more generous tax credits enhance the effect of grants and the two subsidy types are complements. If it is lower, they are substitutes, as the more generous tax credits dampen the grant effect.

Although larger firms are not the core focus of this paper, it is worth discussing the validity of the research design. One assumption is that there are no other policies generating different R&D incentives for firms around the tax credit generosity threshold. This is indeed the case. Small- and medium-sized enterprises do often receive special treatment, but the standard size requirements to qualify as a SME in other policies are half of those that are applied by the R&D tax credit policy.

Second, firms must not select into the higher tax credit rates, such as by strategically downsizing so that they fall below the threshold. Savvy firms exhibiting this behavior may differ systematically from those that do not manipulate their size, making firms just above

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

the threshold a poor control group. I check whether this appears to be happening by plotting the firm size distribution density in Appendix Figure B.2. Visually, there does not appear to be a discontinuity, and a formal McCrary test also provides no evidence of bunching.[30]

Third, the threshold must not have been endogenously chosen. I explore this by testing for continuity in observable covariates around the threshold in pre-policy years. Appendix Table C.8 presents mean values for several R&D-related variables in years prior to 2008. I find no statistically significant differences in R&D expenditures, the proportion of R&D that is funded by the government, turnover per employee, or expenditures specifically on basic and applied research, suggesting that firms did not differ systematically in their R&D activities before the tax credit threshold was implemented.[31]

Lastly, although the causal effect of grant funding cannot be identified in this case, the difference in the grant effect is driven by the exogenous variation in the tax credit rate. As long as the direction and magnitude of the endogeneity of grant funding does not differ systematically for firms just below and above the tax credit threshold, the discontinuity in the grant funding effect should provide reasonable insight into whether the subsidies are complements. Furthermore, since one of the primary concerns about grant funding endogeneity is that more innovative firms are those that are also more likely to win grant competitions, the results from the covariate balance tests in Appendix Table C.8 provide some assurance that the endogeneity is similar for firms around the threshold.

Results for Larger Firms. Table 6 provides the subsidy interaction effects for larger firms when limiting the sample to various windows around the threshold. The grant effects for those under and over the threshold are presented in odd- and even-numbered columns, respectively, and the difference in the effects are in the bottom row, capturing the interaction between tax credits and grants. The subsidy interaction effect is consistently negative and statistically significant, suggesting that the subsidies are substitutes, if anything. In the most conservative case (Columns 3 and 4), the more generous tax credits cut the effect of grants in half.

[TABLE 6 HERE]

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

[31]I test for statistically significant differences using t-tests.

To provide further confidence in the results, I conduct the same analysis but split the dependent variable into capital and non-capital R&D expenditures. Most R&D capital expenditures do not qualify for tax credits in the UK, so the substitution effect should primarily occur for non-capital expenditures. This is what I find (see Table 7). The effect of grants is cut in half for non-capital expenditures, consistent with the baseline finding, but there is no interaction effect for capital expenditures.

[TABLE 7 HERE]

I conduct a few final robustness checks. First, I test whether the grant funding effect is smooth across arbitrary pseudo-thresholds where there is no difference in the tax credit rates and should therefore find no interaction effect. These results are presented in Appendix Table C.9 when imposing cutoffs at 200, 250, 750, and 800 employees. There are no statistically significant interactions detected and the magnitude of the differences are small.

Next, I use additional lagged years to define tax credit generosity treatment. In the baseline, I only use the current year's employment, but eligibility formally requires firms to fall under the thresholds for two consecutive years.[32] Appendix Table C.10 presents results when defining tax credit generosity status according to the preceding years' employment as well. Columns 1 and 2 use just the previous year's employment, Columns 3 and 4 use both the current year and the previous year, and Columns 5 and 6 use the current year and the two previous years. The negative interaction effects increase in magnitude.

Lastly, I use increasingly flexible running variables and provide the results in Appendix Table C.11. The baseline results are provided in Columns 1 and 2 for reference, quadratic polynomials are used in Columns 3 and 4, and cubic polynomials are included in Columns 5 and 6. The results hold and are similar to the baseline.

6 Conclusion

Fostering innovation is an increasingly urgent policy priority amid the recent productivity growth declines experienced by many developed countries. Governments globally are revisiting their industrial strategies, and finding ways to invigorate innovative activity has been

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

at the forefront of these plans. In the U.S., for example, President Biden's budget requests have incorporated all-time high levels of funding for R&D, and the UK has set long-terms goals for increasing private sector R&D as well.

Yet understanding how to design incentives to reach these ambitions remains a long-standing challenge. Many countries offer some combination of direct grants and fiscal incentives, and there is indeed growing evidence that they increase R&D and innovation. But as firms frequently tap into both, it is also important to understand whether they are complements or substitutes, as this can impact the marginal return to each of them.

In this paper, I present new evidence on this question by implementing two quasi-experimental research designs to estimate the effects of grant and tax credit interactions on R&D, finding that these instruments are complements for small firms and substitutes for larger firms in the United Kingdom. Increasing tax credit rates enhances the effect of grant funding for small firms and dampens it for larger firms. Financing constraints seem to be a key driver of the complementary relationship. While previous work has found that financing constraints can explain large effects of grants alone, my results suggest that tax credits may also help address this by enhancing the effects of grant funding. Furthermore, they highlight the importance of considering firm size heterogeneity in policy design.

Policy interactions are also ubiquitous across many economic settings. My findings may therefore also be of interest to other fields, especially when firm size is relevant to the implementation or implications of policies that interact.

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MAIN TEXT TABLES

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

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

Panel B: Average Tax Credit Benefits and Changes

	2008-2012	2013-2017	% Change
Profit-making	0.21	0.26	
Loss-making	0.12	0.18	
Average	**0.165**	**0.22**	**33%**

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

Table 2: Innovate UK Grant Awards and Summary Statistics

	Full Sample	<100 Empl.	10 to 90 Empl.	20 to 80 Empl.
	(1)	(2)	(3)	(4)
Panel A: Grant Awards				
No. of Unique Grants	10,029	1,797	1,123	721
No. of Unique Firms	6,340	1,377	812	533
Panel B: Funding Amounts				
Grant Amount (£000s)	£227.49	£210.31	£236.67	£240.38
	(£1,363)	(£382.34)	(£430.10)	(£442.49)
Total Project Cost Funded (%)	57.8%	60.3%	57.4%	60.0%
	(17.9%)	(17.2%)	(17.2%)	(17.8%)
No. of Observations	9,913	1,784	1,113	715
Panel C: Main Outcome Variable				
R&D Expenditures (£000s)	£166.33	£123.92	£160.96	£179.16
	(£938.82)	(£657.47)	(£772.48)	(£770.57)
No. of Observations	22,071	3,337	2,267	1,534

Notes: Table provides summary statistics for firms receiving Innovate UK grants between 2008 and 2017. Panel A provides information on the number of grants and awardees and Panels B and C provide mean values and standard deviations (in parentheses) of funding levels and R&D expenditures. Only firm-year observations when grants are received from 2008 to 2017 are included in Panels A and B. In Panel C, observations for the two years following a grant are also included, consistent with the baseline estimation sample.

Table 3: Main Results: Effect of Grant and Tax Credit Interactions on R&D

Dependent Variable:	R&D	R&D	R&D	R&D
	(1)	(2)	(3)	(4)
Treated * Post 2012	366.11*	356.75*	383.00**	429.43**
	(187.47)	(183.42)	(183.73)	(183.51)
Treated	-130.66	-101.30	94.07	56.36
	(334.79)	(329.81)	(283.53)	(285.90)
Post 2012	465.76**			
	(231.44)			
Firm FEs	x	x	x	x
Year FEs		x	x	x
Year x Industry FEs			x	x
Controls				x
Observations	1,375	1,375	1,230	1,208
No. of Firms	443	443	401	394
Mean Dep. Var.	196.49	196.49	216.01	218.02

Notes: Dependent variable is total R&D expenditures (£000*s*). Sample includes observations for the grant year and the two years that follow for firms with 20 to 80 employees in the year before they win a grant (conditional on meeting the total assets or turnover criteria as well). Treatment and running variables are defined based on employment in the year before they win the grant. Additional controls include (real) total assets and current liabilities. Standard errors are clustered by industry. Asterisks denote *p <0.10, **p <0.05, ***p <0.01.

Table 4: Unlikely Mechanisms: Proposed Project Costs, Type of Research, and Preferential Treatment of Previous Winners

Dependent Variable:	log(Project Cost)	R&D	Feasibility	Prototype	Received	R&D
	(1)	(2)	(3)	(4)	(5)	(6)
Treated * Post 2012	-0.30	585.39***	0.00	-0.05	-0.18	818.34**
	(0.37)	(207.43)	(0.13)	(0.07)	(0.31)	(309.92)
Treated	-0.33	116.51	-0.08	-0.10	-0.21	210.58
	(0.44)	(320.75)	(0.20)	(0.09)	(0.28)	(306.64)
Firm FEs	x	x	x	x	x	x
Year FEs	x	x	x	x	x	x
Year x Industry FEs	x	x	x	x	x	x
Controls	x	x	x	x	x	x
Observations	1,208	1,208	1,208	1,208	894	1,208
No. of Firms	394	394	394	394	326	394
Mean Dep. Var.	4.02	218.02	0.16	0.09	0.33	218.02

Notes: Dependent variable is log(project) cost in Column 1 and R&D in Columns 2 and 6. In Columns 3 and 4, the dependent variables are indicators equal to one if the project is a feasibility study or for developing a prototype, respectively. In Column 5, it's an indicator equal to one if the firm received a grant. Sample includes observations for the grant year and the two years that follow for firms with 20 to 80 employees in the year before they win a grant (conditional on meeting the total assets or turnover criteria as well). Treatment and running variables are defined based on employment in the year before they win the grant. Additional controls include (real) total assets and current liabilities. Standard errors are clustered by industry. Asterisks denote *p <0.10, **p <0.05, ***p <0.01.

Table 5: Effects of Subsidy Interactions on Constrained vs. Unconstrained Firms

Outcome Variable:	Short Term Debt		Operating Profit		Available Funds	
	Constrained	Unconstr.	Constrained	Unconstr.	Constrained	Unconstr.
	(1)	(2)	(3)	(4)	(5)	(6)
Treated * Post 2012	1037.32**	-672.11	1337.24***	196.17	1284.39***	414.53
	(414.98)	(461.21)	(322.68)	(323.17)	(278.25)	(397.26)
Treated	-20.82	1027.92**	37.46	-227.01	156.89	-897.52
	(644.85)	(457.85)	(506.08)	(282.12)	(507.91)	(630.00)
Firm FEs	x	x	x	x	x	x
Year FEs	x	x	x	x	x	x
Year x Industry FEs	x	x	x	x	x	x
Controls	x	x	x	x	x	x
Observations	372	721	402	681	433	657
No. of Firms	123	254	129	246	139	239
Mean Dep. Var.	243.25	214.65	464.47	96.48	441.99	102.44

Notes: Dependent variable is R&D expenditures (£000*s*). Table provides results from estimating the subsidy interaction effects separately for firms under and over the median value of financing constraint proxies in the baseline estimation sample (short-term debt, operating profits, and available funds). Constrained firms are included in the odd-numbered columns and less constrained firms are in even-numbered columns. Sample includes observations for the grant year and the two years that follow for firms with 20 to 80 employees in the year before they win a grant (conditional on meeting the total assets or turnover criteria as well). Additional controls include (real) total assets and current liabilities. Standard errors are clustered by industry. Asterisks denote *p <0.10, **p <0.05, ***p <0.01.

Table 6: Grant and Tax Credit Interaction Effects on R&D for Larger Firms

Sample:	150 to 850 empl.		250 to 750 empl.		350 to 650 empl.	
	<500	≥ 500	<500	≥ 500	<500	≥ 500
Outcome Variable:	R&D	R&D	R&D	R&D	R&D	R&D
	(1)	(2)	(3)	(4)	(5)	(6)
Direct Subsidies (£000s)	2.539***	6.910***	3.229***	6.610***	2.287***	7.901***
	(0.400)	(1.534)	(0.607)	(1.366)	(0.220)	(1.855)
No. of Observations	1,506	761	848	635	488	409
Difference at Threshold	**-4.371*** **		**-3.381** **		**-5.614*** **	
	(1.585)		**(1.495)**		**(1.868)**	

Notes: Dependent variable is R&D expenditures (£000*s*). The first row of each column reports the effect of direct funding using OLS in separate regressions for firms below (odd-numbered columns) and above (even-numbered columns) the tax credit generosity threshold while using an increasingly narrow window around the cutoff. 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.

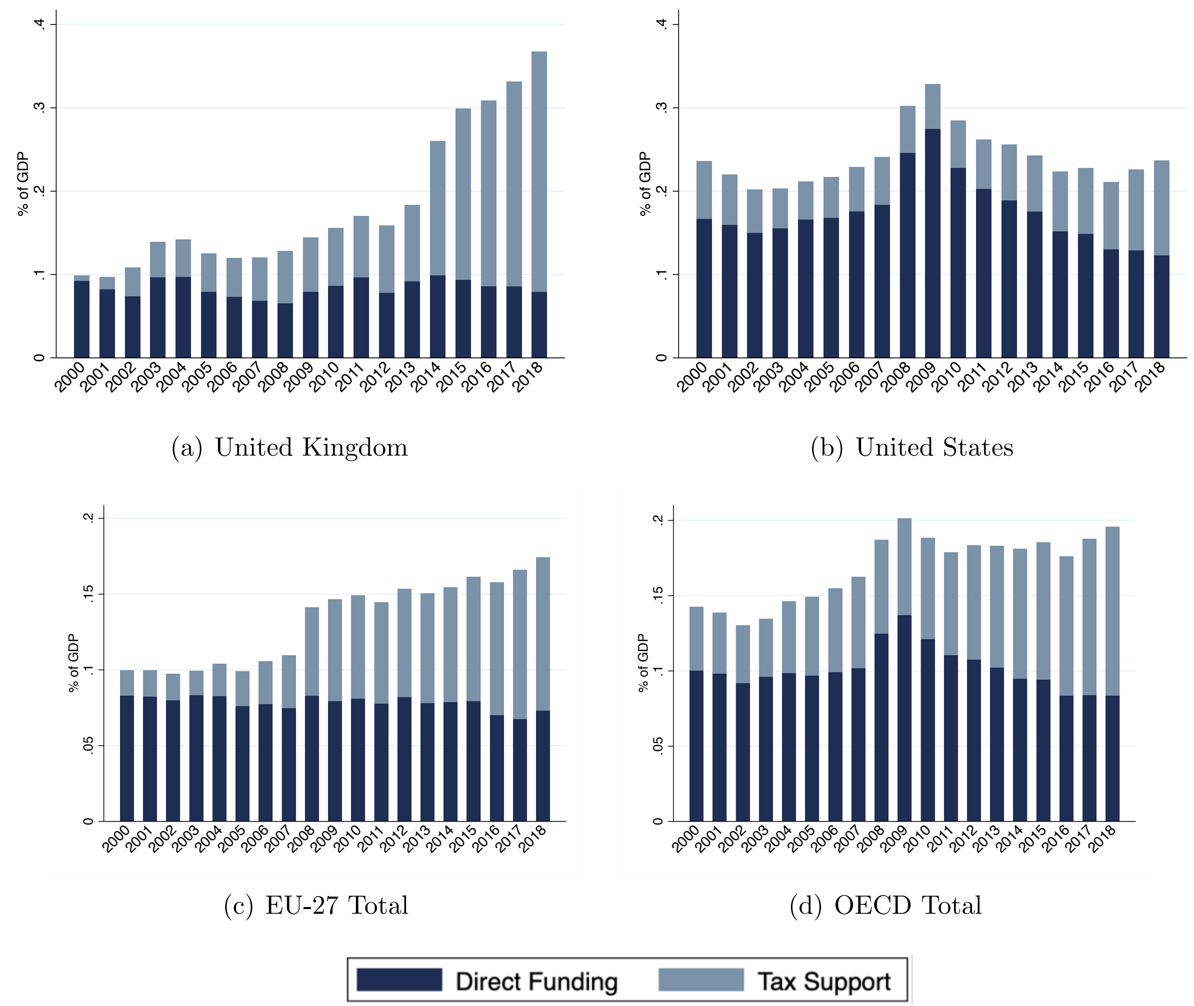
Table 7: Effects on Capital vs. Non-Capital R&D Expenditures for Larger Firms

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

Notes: Dependent variables are capital (Columns 1-2) and non-capital (Columns 3-4) R&D expenditures (£000*s*). Capital expenditures include those on land, buildings, equipment, and machinery. Non-capital expenditures mostly include salaries for R&D workers. The first row of each column reports the effect of direct funding for firms below and above the tax credit generosity threshold for those with 250 to 750 employees. The final row shows the difference in effects. All specifications include controls for employment, age, distance to funding agency HQ, total value of subsidies allocated to each industry-year, and fixed effects for year, business structure, product group, and industry. Standard errors are clustered by industry. Asterisks denote *p <0.10, **p <0.05, ***p <0.01.

MAIN TEXT FIGURES

Figure 1: Government Direct Funding and Tax Support for Business R&D as a Percentage of GDP (2000-2018)



(a) United Kingdom

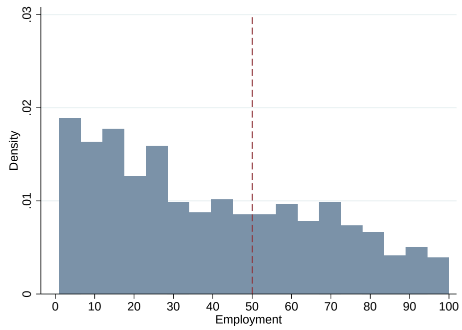
(b) United States

(c) EU-27 Total

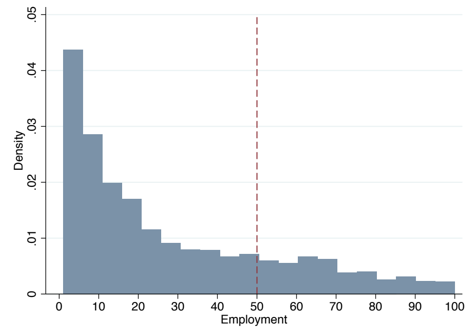
(d) OECD Total

Note: Created using data from the OECD Main Science and Technology Indicators database.

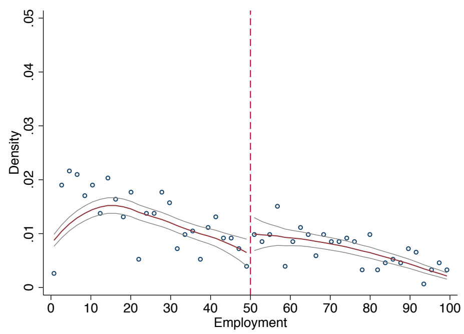
Figure 2: Density of Firms Around Grant Generosity Threshold in Pre- and Post-Tax Credit Rate Change Periods



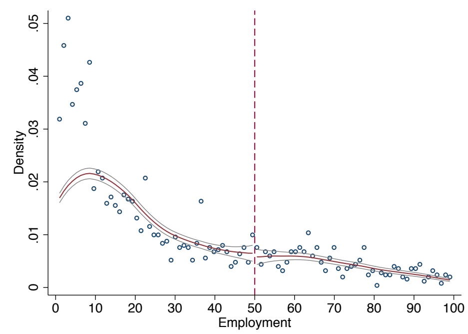
(a) Size Distribution (2008-2012)



(b) Size Distribution (2013-2017)



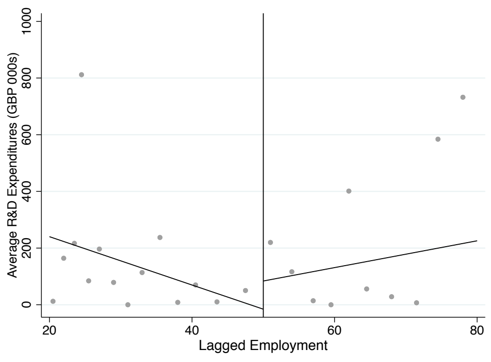
(c) McCrary Density Test (2008-2012)



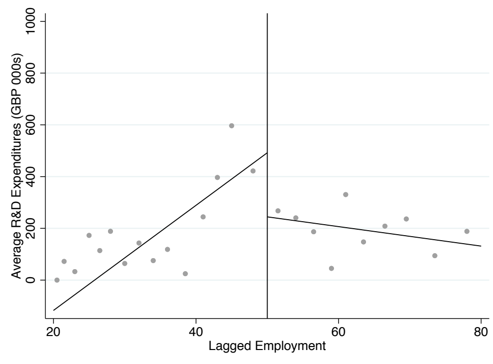
(d) McCrary Density Test (2013-2017)

Note: Firm size distributions before the tax credit increased (Panels A and C) and after (Panels B and D). Includes firms in estimation sample with fewer than 100 employees. When carrying out formal McCrary tests, the log difference in the density height is 0.491 with a standard error of 0.283 in Panel C and -0.112 with a standard error of 0.145 in Panel D. Neither difference is statistically significant, and they are not statistically from each other (t-statistic for the difference is 0.266).

Figure 3: Graphical Depiction of Difference-in-Discontinuity in R&D Expenditures



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



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

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

A Appendix: Data Preparation—For Online Publication Only

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

A.1 Data Preparation for Small Firm Analysis

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

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

The resulting grant-level data set contains 14,497 grants allocated to 6,737 unique firms from 2005 through 2017. Once collapsing to the firm-year level to match the data to the financial data, there are 10,787 observations, and only 353 do not match (a 97% match rate). I then limit the sample to 2008-2017 because the program was only providing a small number of grants in its first few years. The final sample includes 22,071 observations with 10,029 grants across 6,340 unique firms.

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

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

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

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

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

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

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

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

A.2 Data Preparation for Larger Firm Analysis

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

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

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

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

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

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

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

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

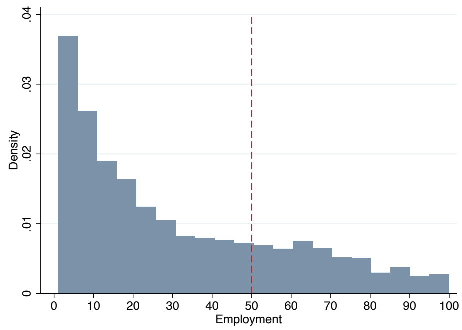
The BSD annual datasets include variables such as local unit-level and enterprise-level employment, turnover, company start-up date, postcodes, and the Standard Industrial Classification (SIC). I aggregate variables to the enterprise group level. If the observation is missing an enterprise number and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

Final Data Sample Preparation.—An additional control variable that I construct is the firm's distance from the UK's primary funding agency's headquarters in London. This helps control for knowledge spillovers, since the vast majority of R&D in the UK happens in or near London. To do this, I obtained a full list of the UK's postcodes that included their latitudes and longitudes. I take just the outward code plus the first character of the inward code to identify the neighborhood of the postcode (due to limitations on the geocoding package that I use) and average the latitudes and longitudes for each modified postcode. I then find the travel distances, measured in kilometers and driving minutes, of each modified postcode to the London headquarters of the UK's funding agency's latitude and longitude. Applying this procedure using post codes from BERD and BSD provide distance measures for all but 0.1 percent of the BERD data. For those that do not match, I interpolate the missing values with the average values of the distance variables within postal areas (the first two characters of the firm's postcode).

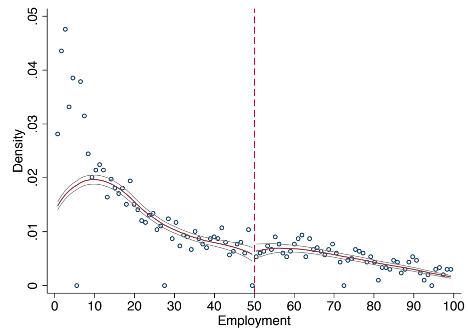
A few final steps are taken to prepare the data. First, all expenditure and financial variables are converted into real 2010 terms using the World Bank's Consumer Price Index. Observations associated with inactive firms are dropped from the sample, which results in dropping only 72 observations. I omit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

B Appendix: Additional Figures—For Online Publication Only

Figure B.1: Density of Firms Around Grant Generosity Threshold—All Years



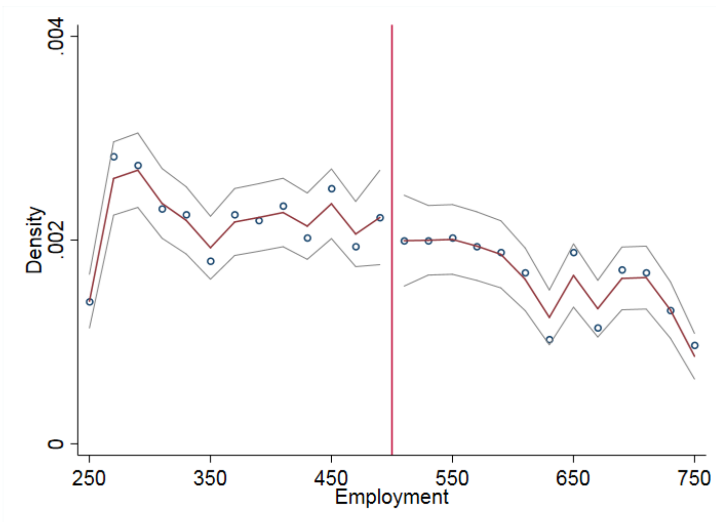
(a) Size Distribution (2008-2017)



(b) McCrary Density Test (2008-2017)

Note: Firm size distribution (Panel A) and McCrary test (Panel B) for a discontinuity in the distribution density of employment at the small firm employment threshold for all years in sample. Includes sample used in main regressions when including firms with fewer than 100 employees. The log difference in the density height is 0.121 with a standard error of 0.163, which is not statistically significant.

Figure B.2: Density of Firms Around Tax Credit Threshold (Larger Firms)



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

C Appendix: Additional Tables—For Online Publication Only

Table C.1: R&D Tax Credit Rates for Large Firms

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

Notes: Table provides R&D enhancement rates for firms with more than 500 employees, the main corporate tax rate, the percent R&D tax credit benefit that this translates into, and the percentage point difference in benefits relative to SMEs paying the main corporate tax rate. The tax credit rate is the product of the enhancement and corporate tax rates.

Table C.2: Balance in Baseline Covariates and Likelihood of Winning a Grant

Dependent Variable:	Age		Oper. Cash		Received Grant	
	(1)	(2)	(3)	(4)	(5)	(6)
Treated * Post 2012		-0.197		14.612		-0.239
		(0.584)		(594.399)		(0.327)
Treated	-0.596	-0.444	-149.4	-209.3	-0.344	-0.169
	(0.398)	(0.559)	(262.530)	(643.683)	(0.236)	(0.310)
Firm FEs	x	x	x	x	x	x
Year FEs	x	x	x	x	x	x
Year x Industry FEs	x	x	x	x	x	x
Controls	x	x	x	x	x	x
Observations	1,208	1,208	421	421	1,208	1,208
No. of Firms	394	394	131	131	394	394
Mean Dep. Var.	20.9	20.9	-194.1	-194.1	0.442	0.442

Notes: In Columns 1-4, dependent variables are age and operating cash in the year before winning a grant. In Columns 5-6, the dependent variable is an indicator equal to one if the firm received a grant that year. Sample includes observations for the grant year and the two years that follow for firms with 20 to 80 employees in the year before they win a grant (conditional on meeting the total assets or turnover criteria as well). Treatment and running variables are defined based on employment in the year before they win the grant. Standard errors are clustered by industry. Asterisks denote *p <0.10, **p <0.05, ***p <0.01.

Table C.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.	Firms with rateable value less than £15k or business uses only one property.
Corporate Taxes	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. Relief 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	Commitment to help small businesses grow.	No firm size definitions that align with the Innovate UK definitions.
British Business Bank	A business development bank committed to making finance markets work better for small businesses.	Support programs for start-ups and small businesses in general with no noticeable advantages to firms that align with the firm size definitions for grant generosity.
Employer NI Contributions	Employers pay secondary national insurance contributions to HMRC.	Rates are determined by profits as opposed to employment, turnover, or total assets.
Value Added Tax	VAT registration is required for firms of a certain size.	The threshold for VAT registration is £85k.
Pay As You Earn	Payment by employers as part of the payroll so that the HMRC can collect income tax and national insurance.	Income tax rates depend on how much of taxable income is above personal allowance, and rates are determined by earnings.
Export Credits Guarantee Scheme	Encourages exports by SMEs by ensuring successful implementation of scheme.	Applies to all SMEs, not just small firms.
Loan Guarantees for SMEs	Government agreement with large banks to extend loans to small businesses in the UK, increasing the availability of finance.	Applies to all SMEs, not just small firms.
Enterprise Capital Funds	Financial schemes to address the provision of equity finance to certain firms and to invest in high growth businesses.	Applies to all SMEs, not just small firms.
Business Angel Co-Investment Fund	A £100M investment fund for UK businesses.	Applies to all SMEs, not just small firms.

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

Table C.4: Effect of Grant and Tax Credit Interactions on Ordinary Investment

Dependent Variable:	Ord Inv. (incl. deprec.) (1)	Ord Inv. (excl. deprec.) (2)	ihs(Ord Inv.) (incl. deprec.) (3)	ihs(Ord Inv.) (excl. deprec.) (4)
Treated * Post 2012	766.91	971.91	1.38	2.66
	(511.38)	(618.35)	(1.33)	(3.04)
Treated	-659.23	-782.44	0.27	-0.85
	(506.13)	(558.05)	(2.09)	(2.73)
Firm FEs	x	x	x	x
Year FEs	x	x	x	x
Year x Industry FEs	x	x	x	x
Controls	x	x	x	x
Observations	1,134	1,158	1,134	1,158
No. of Firms	378	381	378	381
Mean Dep. Var.	302.26	111.73	4.21	-0.21

Notes: Dependent variables are measures of non-R&D investment as described in Section 4.3.1. Sample includes observations for the grant year and the two years that follow for firms with 20 to 80 employees in the year before they win a grant (conditional on meeting the total assets or turnover criteria as well). Treatment and running variables are defined based on employment in the year before they win the grant. Additional controls include (real) total assets and current liabilities. Standard errors are clustered by industry. Asterisks denote *$p<0.10$, **$p<0.05$, ***$p<0.01$.

Table C.5: Effects on Probability of Reporting Other Financial Variables

Dependent Variable:	Reported (1)	Reported (2)	Reported (3)	Reported (4)	Reported (5)	Reported (6)
Treated * Post 2012				0.065	0.005	0.155
				(0.107)	(0.006)	(0.170)
Treated	0.034	-0.001	0.062	-0.012	-0.004	-0.046
	(0.072)	(0.001)	(0.070)	(0.072)	(0.005)	(0.117)
Reported Variable:						
Profits	x			x		
Shareholder Funds		x			x	
Cost of sales			x			x
Firm FEs	x	x	x	x	x	x
Year FEs	x	x	x	x	x	x
Year x Industry FEs	x	x	x	x	x	x
Controls	x	x	x	x	x	x
Observations	1,208	1,208	1,208	1,208	1,208	1,208
No. of Firms	394	394	394	394	394	394
Mean Dep. Var.	0.855	0.999	0.692	0.855	0.999	0.692

Notes: Dependent variables are indicators equal to one if the firm reported profits, shareholder funds, or cost of sales. Sample includes observations for the grant year and the two years that follow for firms with 20 to 80 employees in the year before they win a grant (conditional on meeting the total assets or turnover criteria as well). Treatment and running variables are defined based on employment in the year before they win the grant. Additional controls include (real) total assets and current liabilities. Standard errors are clustered by industry. Asterisks denote *$p<0.10$, **$p<0.05$, ***$p<0.01$.

Table C.6: Additional Robustness Checks of Main Results and Falsification Tests

Dependent Variable:	R&D	R&D	R&D	R&D	R&D	R&D
Sample:	10 to 90 Empl.	<100 Empl.	Baseline	Baseline	Baseline	Baseline
	(1)	(2)	(3)	(4)	(5)	(6)
Panel A: Window Width and Polynomial Flexibility						
Treated * Post 2012	405.65***	296.12**	412.29*	1472.63***		
	(143.32)	(146.51)	(205.83)	(480.60)		
Treated	93.97	127.23	252.25	-162.79		
	(183.50)	(166.61)	(261.50)	(857.02)		
Panel B: Effects at Pseudo-Thresholds						
Pseudo-Thresh (30) * Post 2012					-21.59	
					(218.61)	
Pseudo-Thresh (30)					-164.12	
					(475.69)	
Pseudo-Thresh (70) * Post 2012						-98.33
						(305.88)
Pseudo-Thresh (70)						331.97
						(203.73)
Polynomial Flexibility:						
Linear (baseline)	x	x			x	x
Quadratic			x			
Cubic				x		
Firm FEs	x	x	x	x	x	x
Year FEs	x	x	x	x	x	x
Year x Industry FEs	x	x	x	x	x	x
Controls	x	x	x	x	x	x
Observations	1,868	2,587	1,208	1,208	1,803	1,248
No. of Firms	613	879	394	394	646	397
Mean Dep. Var.	201.54	190.94	218.02	218.02	174.61	286.73

Notes: Dependent variable is R&D expenditures (£000*s*). Sample includes observations for the grant year and the two years that follow, and in Columns 1-2, the window around the cutoff is extended to include firms with 10-90 employees and fewer than 100 employees in the year before they receive a grant. The baseline window of 20 to 80 employees is used in Columns 3-6. In Columns 3 and 4, increasingly flexible polynomials are used for the running variable controls. Columns 5 and 6 provide results for falsification tests that impose pseudo-thresholds at 30 and 70 employees rather than the real cutoff of 50 employees. Treatment and running variables are defined based on employment in the year before they win the grant. Additional controls include (real) total assets and current liabilities. Standard errors are clustered by industry. Asterisks denote *p <0.10, **p <0.05, ***p <0.01.

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

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

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

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

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

Notes: Table provides mean values 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 statistically significant differences in the means between firms just below and above the tax credit generosity threshold.

Table C.9: Pseudo Threshold Falsification Tests for Larger Firms

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

Notes: Dependent variable is R&D expenditures (*£000s*). Estimates report the effect of direct funding from separate regressions for firms below and above arbitrary thresholds. Firms with 0 to 400 employees are included in Panel A. Firms with 50 to 450 employees are included in Panel B. Firms with 550 to 950 employees are included in Panel C. Firms with 600 to 1000 employees are included in Panel D. All specifications include controls for employment, age, distance to funding agency HQ, total value of subsidies allocated to each industry-year, and fixed effects for year, business structure, product group, and industry. Standard errors are clustered by industry. Asterisks denote *p <0.10, **p <0.05, ***p <0.01.

Table C.10: Robustness of Larger Firm Results When Using Lagged Employment

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

Notes: Dependent variable is R&D expenditures (*£000s*). The first row of each column reports the effect of direct funding using OLS in separate regressions for firms below and above the tax credit generosity threshold with 250 to 750 employees. Columns 1 & 2 define tax credit treatment based upon the firm's preceding year's employment level being less than 500. Columns 3 & 4 define it based upon both the current and preceding year's employment level meeting the requirement, and in Columns 5 & 6, treatment is defined based upon the current and two preceding years' employment. All specifications also include controls for employment, age, distance to funding agency HQ, total value of subsidies allocated to each industry-year, and fixed effects for year, business structure, product group, and industry. Standard errors are clustered by industry. Asterisks denote *p <0.10, **p <0.05, ***p <0.01.

Table C.11: Robustness to Increasing Polynomial Flexibility for Larger Firms

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

Notes: Dependent variable is R&D expenditures (*£000s*). Estimates report the effect of direct funding from separate OLS regressions for firms below and above the tax credit generosity threshold with 250 to 750 employees while increasing the flexibility of the employment running variable. 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.