Do tax incentives increase firm innovation? An RD Design for R&D

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Abstract

We present the first evidence of the positive causal impacts of research and development (R&D) tax incentives on a firm's own innovation and that of its technological neighbors (spillovers). Exploiting a change in the assets-based size thresholds that determine eligibility for R&D tax relief, we implement a Regression Discontinuity (RD) Design using administrative data. We find statistically and economically significant effects of tax relief on R&D, (quality-adjusted) patenting and ultimately firm size that persist up to seven years after the change. We can rule out R&D tax price elasticities of under 1.1 at the 5% level and argue that our large effects are likely because the treated group are smaller firms that are more likely to be financially constrained. Using our RD Design, we also find causal impacts on technologically close peer firms, implying significant under-investment in R&D from a social perspective.

Keywords: R&D, patents, tax, innovation, spillovers, Regression Discontinuity Design

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1. Introduction

Innovation is recognized as the major source of growth in advanced economies (Romer, 1990, Aghion and Howitt, 1992). However, because of knowledge externalities, private returns on research and development (R&D) are generally thought to be much lower than their social returns, suggesting the need for some government subsidy.[1] Indeed, the majority of OECD countries have tax incentives for R&D and over the last two decades, these incentives have grown increasingly popular, even compared to direct R&D subsidies to firms.[2]

But do R&D tax incentives really increase innovation? In this paper, we identify the causal effects of R&D tax incentives by exploiting a policy reform that raised the size threshold under which firms could access the more generous tax regime for small- and medium-sized enterprises (SMEs). Importantly, the new SME size threshold introduced was unique to the UK R&D Tax Relief Scheme and did not overlap with access to other programs or taxes. This allows us to implement a Regression Discontinuity (RD) Design to assess the differences in innovation activity around the new SME threshold. We assemble a new database linking the universe of UK companies with their confidential tax returns (including R&D expenditures) from HMRC (the UK IRS), their patent filings in all major patent offices in the world, and their financial accounts. Our data are available for the periods before and after the R&D tax change, allowing us to analyze the causal impact of the tax credit up to seven years after the policy change.

A key advantage of our firm-level patent dataset is that it enables us to assess the effect of tax incentives not only on R&D spending (an input) but also on innovation outputs.[3] A long-standing concern us that tax incentives could increase observed R&D without having much effect on innovation because firms relabel existing activities to take advantage of the tax relief (e.g., Chen et al., 2019) or only expand very low-quality R&D projects. We can directly examine the quality of these innovations through various measures of patent value, such as future citations received and the number of countries that a patent obtains protection.

We find large effects of the tax relief on both R&D and patenting activity. Following the policy

[1] Typical results find marginal social returns to R&D between 30% and 50% compared to private returns between from 7% to 15% (Hall, Mairesse, and Mohnen, 2010).

[2] In 2018, 80% of OECD countries had some type of additional R&D tax relief, whereas only 40% did in 2000 (OECD 2019). One reason for this shift is that subsidizing R&D through the tax system rather than direct grants reduces administrative burden and mitigates the risk of "picking losers" (e.g., choosing firms with low private and social returns due to political connections, as in Lach, Neeman, and Schankerman, 2017)

[3] There is a large literature on the effects of public R&D grants on firm and industry outcomes such as González, Jaumandreu, and Pazó (2005), Takalo, Tanayama, and Toivanen (2013), Einiö (2014), Goodridge et al. (2015), Jaffe and Le (2015), and Moretti, Steinwender, and Van Reenen (2019). The earlier literature is surveyed in David, Hall, and Toole (2000).

change, R&D more than doubled in firms below eligibility threshold (who were more likely to benefit from the SME Scheme), followed by about a 60% increase in patenting. We can rule our R&D elasticities with respect to user costs of less than 1.1 at the 5% significance level.[4] Our relatively high elasticities are likely because the sub-population targeted in our design is composed of smaller firms than those typically studied in the literature. These firms are more likely to be financially constrained and therefore more responsive to R&D tax incentives. We confirm this intuition by showing the response was particularly strong for firms in industries more likely to suffer from financial frictions.[5] Simple partial equilibrium calculations suggest that over 2006-11 the UK R&D Tax Relief Scheme induced about $2 of private R&D for every $1 of taxpayer money, and that aggregate UK business R&D (BERD) would have been about 13% lower in the absence of the policy.[6]

The main economic rationale given for more generous tax treatment of R&D is that there are technological externalities, so that the social returns to R&D exceed the private returns. Our design also allows us to estimate the causal impact of tax policies on R&D spillovers, i.e., their effect on innovation activities of firms who were *technologically connected* to policy-affected firms. We find evidence that the R&D induced by the tax policy generated positive spillovers on innovations by technologically related firms, especially in smaller technology classes. Focusing on these smaller peer groups is exactly where we expect our design to have power to detect spillovers (see Angrist, 2014 and Dahl, Løcken, and Mogstad, 2014).

The paper is organized as follows. First, we offer a brief literature review; then Section 2 details the institutional setting; Section 3 explains the empirical design; and Section 4 describes the data. Section 5 reports policy affects R&D and innovation; Section 6 presents the results on R&D technology spillovers, and Section 7 discusses the magnitudes and economic implications of the policy's effects. Section 8 offers some concluding remarks. Online Appendices provide more institutional details (A), a deeper data description (B), robustness checks and extensions (C), and econometric details (D-F).

Related literature. Most directly, our paper contributes to the literature that seeks to evaluate the effects of tax policies on R&D. Earlier evaluations conducted at the state or macro-economic

[4] See surveys by Becker (2015), OECD (2013), or Hall and Van Reenen (2000) on R&D to user cost elasticities. The mean elasticities are usually between one and two whereas our mean results are about twice as large.
[5] Financial constraints are more likely to affect R&D than other forms of investment (Arrow, 1962). This is because (i) information asymmetries are greater, (ii) R&D is mainly researchers who cannot be pledged as collateral, and (iii) external lenders may appropriate ideas for themselves.
[6] See Akcigit, Hanley, and Stantcheva (2017) and Acemoglu et al. (2018) for rigorous discussion of optimal taxation and R&D policy in general equilibrium.

level face the problem that policy changes often coincide with many unobserved factors that may influence R&D. Recent studies use firm-level data and more credible causal designs, but tend to focus solely on the impact on R&D expenditures.[7] Like us, Rao (2016) uses administrative tax data and looks at the impact of US tax credits on R&D. She uses the changes in the Federal tax rules interacted with lagged firm characteristics to generate instrumental variables for the firm-specific user cost of R&D. Guceri (2018) and Guceri and Liu (2019) use a difference-in-differences strategy to examine the introduction and change in the UK R&D tax regime.[8] Bøler, Moxnes, and Ulltveit-Moe (2015) employ strategy to investigate how the introduction of R&D tax credit in Norway affected profits, intermediate imports, and R&D. These papers find effects of tax incentives on R&D, but do not look at direct innovative outcomes as we do.[9] Chen et al. (2019) is perhaps the closest paper to ours. The authors examine the impact of tax changes in corporate tax regulations on R&D and other outcomes in a sample of Chinese firms using an RD Design. They find positive impacts, although about 30% of the additional R&D was relabeling.

Second, we relate to the literature that examines the impact of research grants using ratings given to grant applications as a way of generating exogenous variation around funding thresholds. Jacob and Lefgren (2010) and Azoulay et al. (2019) examine NIH grants, Ganguli (2017) looks at grants for Russian scientists, and Bronzini and Iachini (2014) and Bronzini and Piselli (2016) study firm R&D subsidies in Italy. Howell (2017) uses the ranking of US SBIR proposals for energy R&D grants and finds significant effects of R&D grants on future venture capital funding and patents. Like us, she also finds bigger effects for small firms.[10] However, none of these papers examines tax incentives directly.

Third, our paper also contributes to the literature on the effects of R&D on innovation (see the Hall, Mairesse, and Mohnen, 2010 survey or Doraszelski and Jaumandreu, 2013, for example). We find that policy-induced R&D has positive causal effects on innovation, with elasticities that are underestimated in conventional OLS approaches. Although there is also a large literature on R&D

[7] On more aggregate data, examples include Bloom, Griffith, and Van Reenen (2002), Wilson (2009), and Chang (2018). On the firm-level side, examples include Mulkay and Mairesse (2013) on France, Lokshin and Mohnen (2012) on the Netherlands, McKenzie and Sershun (2010) and Agrawal, Rosell, and Simcoe (2020) on Canada, and Parisi and Sembenelli (2003) on Italy.

[8] Although complementary to our paper, they look only at UK R&D and not at innovation outcomes or spillovers. Methodologically, they do not use an RD Design and condition on post-policy R&D performing firms.

[9] See also Czarnitki, Hanel, and Rosa (2011), Cappelen, Raknerud, and Rybalka (2012), and Bérubé and Mohnen (2009) who look at the effects of R&D tax credits on patents and/or new products. Mamuneas and Nadiri (1996) look at tax credits, R&D, and patents. These papers, however, have less of a clear causal design.

[10] Larger program effects for smaller firms are also found in several other papers such as Mahon and Zwick (2017) and Wallsten (2000) for the US, González et al. (2005) for Spain, Lach (2002) for Israel, Bronzini and Iachini (2014) for Italy, and Gorg and Strobl (2007) for Ireland.

spillovers (e.g., Bloom, Schankerman, and Van Reenen, 2013, Griliches, 1992, Jaffe, Trajtenberg and Henderson, 1993), we are, to our knowledge, the first to provide evidence for the existence of technology spillovers in a RD Design.

Finally, we connect to an emerging field, which looks at the role of both individual and corporate tax on individual inventors (rather than the firms that they work for). This literature also appears to be finding an important role for taxation on mobility, quantity, and quality of innovation. In particular, Akcigit et al. (2018) find major positive effects of individual and corporate income tax cuts on innovation using panel data on US states between 1940 and 2000.[11]

2. The UK R&D Tax Relief Scheme

Full institutional details are in Appendix A, but we sketch the relevant details here. From the early 1980s the UK business R&D to GDP ratio fell, whereas it rose in most other OECD countries. In 2000, an R&D Tax Relief Scheme was introduced for small and medium enterprises (SMEs) and was extended to cover large companies in 2002 (but SMEs continued to enjoy more generous R&D tax relief). The policy cost the UK government £1.4 billion in 2013 alone (Fowkes, Sousa, and Duncan, 2015).

The tax relief is based on the total amount of R&D, i.e., it is volume-based rather than calculated as an increment over past spending like the US R&D tax credit. It works mostly through enhanced deduction of R&D from taxable income, thus reducing corporate tax liabilities.[12] At the time of its introduction, the scheme allowed SMEs to deduct an additional *enhancement rate* of 50% of qualifying R&D expenditure from taxable profits (on top of the 100% deduction that applies to any form of current expenditure). If an SME was not making profits, it could surrender enhanced losses in return for a payable tax credit. This feature is particularly beneficial to firms that are liquidity constrained and thus may not be making enough profits to benefit from enhanced tax deduction. We will present evidence in line with the idea that the large effects we observe were linked to the alleviation of such financial constraints. Large companies had a less generous enhancement rate of 25% of their R&D and could not claim the refundable tax credits in case of losses.

The policy used the definition of an SME recommended by the European Commission (EC)

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[11] A difference with our work is that some of their effects could come from geographical relocation within the country rather than an overall rise in aggregate innovation (although they do use a state boundary design to argue that not all of the effects are from relocation). By contrast, our policy is nation-wide. For other work considering individual data on inventors and tax see Akcigit, Baslandze and Stantcheva (2016) and Moretti and Wilson (2017).

[12] Only current R&D expenditures, such as labor and materials, qualify for the scheme. However, since capital only accounts for about 10% of total R&D, this is less important.

throughout most of the 2000s. This was based on total assets, sales, and employment. It also took into consideration company ownership structure and required that in order to change its SME status, a company must fall in the new category for two consecutive years. (See Appendix A.2 for further details on the SME definition.)

We focus on the major change to the scheme that commenced from August 2008 (Online Table A1). The SME assets threshold was increased from €43m to €86m, the sales threshold from €50m to €100m, and employment threshold from 249 to 499.[13] Because of these changes, a substantial number of firms that were only eligible for the large company rate according to the old definition then became eligible for the SME rate. In addition to the change in SME definition, the UK government also increased the enhancement rate for both SMEs and large companies in the same year. This increase was from 50% to 75% for SMEs and from 25% to 30% for large companies. This change induced a reduction in the tax-adjusted user cost of R&D for the newly eligible SMEs, from 0.19 down to 0.15, whereas the R&D user cost of firms that remained large companies was basically unchanged (Online Table A2).

We examine the impact of this sharp jump from 2008 onwards in tax-adjusted user cost of R&D at the new SME thresholds. There are several advantages of employing this reform instead of the earlier changes. First, unlike the previous thresholds based on the EC's definition, which were extensively used in many other support programs targeting SMEs, the thresholds introduced in 2008 were specific to the R&D Tax Relief Scheme. This allows us to recover the effects of the R&D Tax Relief Scheme without confounding them with the impact of other policies. Second, identifying the policy impacts around newly introduced thresholds mitigates concerns that tax planning may lead to endogenous bunching of firms around the thresholds. Indeed, we show that pre-2008, there was no bunching around these thresholds and predetermined covariates were all balanced at the cutoffs. This is important, as although the new policy's effective date of August 1st, 2008 was only announced less than a month earlier on July 16th, 2008, aspects of the policy were laid out in the Finance Act 2007, so firms could have responded in advance. Information frictions, adjustment costs, and policy uncertainty mean that this adjustment was likely to be sluggish, especially for the SMEs we study.[14] We thus focus on the 2007 values of firm financial variables, as they matter for the firm's SME status in 2009 by the two-year rule, but were unlikely affected by tax-planning incentives.

[13] The other criteria laid down in the EC's 2003 recommendation (e.g., two-year rule) were maintained in the new provision in the Finance Act 2007. This act, however, did not appoint a date on which new ceilings became effective.
[14] Sluggish adjustment to policy announcements is consistent with many papers in the public finance literature (e.g., Kleven and Waseem, 2013).

Among the three determinants of SME status, we focus on total assets to avoid the issue of selective missing values among sales and employment. We will discuss this data issue in detail in subsection 4.1 and show that results remain qualitatively similar when sales and employment are taken into consideration in alternative specifications in Online Appendix C.6.

3. Empirical strategy using RD Design

R&D regression. We first consider a reduced-form RD equation of the form:

$$R_{i,t} = \alpha_{1,t} + \beta_t^R E_{i,2007} + f_{1,t}\left(z_{i,2007}\right) + \varepsilon_{1i,t}, \tag{1}$$

where $R_{i,t}$ is the R&D expenditure of firm i in year t, $E_{i,2007}$ a binary indicator equal to one if 2007 assets does not exceed the threshold value and zero otherwise, and $f_{1,t}\left(z_{i,2007}\right)$ polynomials of the running variable, namely assets in 2007. In an RD Design, the identification assumption requires that the distributions of all predetermined variables are smooth around the cutoff, which is testable on observables. This identification condition is guaranteed when firms cannot precisely manipulate the running variable (Lee, 2008, Lee and Lemieux, 2010).[15] Under this assumption, $E_{i,2007}$ is as good as randomly assigned at the threshold.

As described in Section 2, $E_{i,2007}$ is among the criteria used to determine firm *i*'s SME status. Equation (1) thus represents the reduced-form of a fuzzy RD Design in which $E_{i,2007}$ is the instrument for firm i's actual eligibility for the more generous SME Scheme ($SME_{i,t}$). We cannot directly implement this fuzzy RD Design, as $SME_{i,t}$ is not observed for the vast majority of firms that do not perform any R&D (see subsection 4.1). Instead, the coefficient β^R captures the reduced-form effect of being below the assets threshold, and therefore more likely eligible for the SME Scheme, on a firm's R&D spending at this threshold. It presents a lower bound for the true effect of the SME Scheme. In subsection 7.2, we describe in more detail our strategy to derive this true effect from β^R and available information on the SME status of R&D performing firms.

We estimate equation (1) for both year-by-year outcomes and their average over post-policy years. We also estimate analogous regressions using pre-policy outcomes to assess the validity of the RD Design. The "new SMEs", i.e., those becoming SMEs thanks to the new definition, were allowed SME tax relief rates only on R&D performed after August 2008. Hence, to the extent that firms could plan (or misreport) the timing of R&D, such companies would have an incentive to

[15] Lee and Lemieux (2010)'s "local randomization result", i.e., $\lim_{z_i \to 86-} \mathbb{E}[U_i|E_i = 1] = \lim_{z_i \to 86+} \mathbb{E}[U_i|E_i = 0]$ for any observable or unobservable characteristic U_i of firm *i*, holds under the sufficient condition that there are some (possibly very small) perturbations so that firms do not have full control of their running variable (assets size). That is, even when firms could manipulate their assets, the RD Design identification condition remains valid as long as the manipulation could not be precise.

reduce 2008 R&D expenditures before August and increase them afterwards. To avoid these complexities with the transition year of 2008, we focus on 2009 and afterwards as full policy-on years.

As is standard in RD Designs, we control for separate polynomials of the running variable on both sides of the cutoff. We further follow Gelman and Imbens' (2018) advice to use first order polynomials when higher order coefficients are not statistically significant.[16] As noted above, because of the two-year rule, a firm's SME status in 2009 was partly based on its financial information in 2007. Furthermore, using assets in 2007 as our primary running variable mitigates the concern that there might have been endogenous sorting of firms across the SME threshold. Indeed, Figure 1 shows that firms' 2007 assets distribution was continuous around the 2008 new SME threshold of €86m. The corresponding McCrary test yields a discontinuity estimate (log difference in density height at the SME threshold) of -0.026 with a standard error of 0.088, which is not statistically different from zero. Similar McCrary tests indicate that firms' 2007 sales and employment distributions were also smooth at the respective thresholds. On the other hand, there appears to be some small, but also insignificant, evidence of bunching below the SME thresholds in later year (see Online Appendix C.1).

Patent regression. For innovation outputs, we consider the following analogous reduced-form RD equation:

$$PAT_{i,t} = \alpha_{2,t} + \beta_t^{PAT} E_{i,2007} + f_{2,t}(z_{i,2007}) + \varepsilon_{2i,t}, \tag{2}$$

where the dependent variable $PAT_{i,t}$ is number of patents filed by firm i in year t. We examine the policy impact over a longer period from 2009 to 2015, due to the potential lag between R&D inputs and outputs. Under the same identification assumptions discussed above, β^{PAT} estimates the causal effect of being below the assets threshold, and therefore more likely eligible for the more generous SME Scheme, on a firm's patenting at this threshold. As with R&D, this estimate presents a lower bound for the true effect of the SME Scheme.

IV regression. We also consider the structural patent equation:

$$PAT_{i,t} = \alpha_{3,t} + \gamma_t R_{i,t} + f_{3,t}(z_{i,2007}) + \varepsilon_{3i,t}, \tag{3}$$

which can be interpreted as a "knowledge production function" as in Griliches (1979). Equations (1), (2), and (3) correspond to the first-stage, reduced-form, and structural equations of an RD-based IV model that estimates the returns to additional R&D spending induced by the SME Scheme on firm's patents, using $E_{i,2007}$ as the instrument for R&D. With homogenous treatment

[16] We show in robustness checks that including higher second or third order polynomials produce qualitatively similar results across all specifications, and that higher order coefficients are indeed not statistically different from zero.

effects, the IV estimate delivers the causal effect of R&D on patents; with heterogeneous treatment effects, it captures the causal marginal effect of policy-induced R&D on innovation outputs.[17] Both frameworks require the exclusion restriction that the discontinuity induced exogenous fluctuations in $E_{i,2007}$ did not affect patents through any channel other than qualifying R&D.

Under the identification assumptions discussed earlier, the RD Design guarantees that $E_{i,2007}$ (conditional on appropriate running variable controls) affected innovations only through a firm's eligibility for the SME Scheme, which directly translated into qualifying R&D expenditure. It is possible that firms benefitting from the SME Scheme (i) also increased complementary investment spending in capital or managerial capabilities (even though they would want to classify as much of this spending as qualifying R&D expenditure if possible); or (ii) relabeled existing non-R&D spending as qualifying R&D expenditure in order to claim R&D tax relief. The first channel would bias our estimate of γ upward, while the second channel would bias it downward. Empirically, we do not find evidence of discontinuities in firm's capital expenses, (non-R&D) administrative expenses, or any other expense category besides qualifying R&D at the same threshold in the post-policy period.[18] This suggests that these other channels through which $E_{i,2007}$ could affect innovations are unlikely a first order concern. Relabeling is potentially a harder problem to deal with, but it would affect only R&D expenditures and not patenting activity, which is the main outcome variable we focus on.

Equations (1) and (3) can be derived from optimizing behavior of a firm with an R&D augmented CES production function and Cobb-Douglas knowledge production function (see Online Appendix E.1). In subsection 7.2, we discuss how equation (1) and (2)'s reduced-form estimates can be used to derive the true effects of the SME Scheme and the elasticities of R&D and patents with respect to R&D user cost.

4. Data and sample description

4.1 Data sources

Online Appendix B details our three main data sources: (i) HMRC Corporate Tax returns (CT600) and its extension, the Research and Development Tax Credits (RDTC) dataset, (ii) Bureau Van Dijk's FAME dataset, and (iii) PATSTAT dataset. We give an overview here.

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[17] With heterogeneous treatment effects, IV requires an additional monotonicity assumption that moving a firm's size slightly below the threshold always increases R&D. In this case, γ is the Average Causal Response (Angrist and Imbens, 1995), a generalization of the Local Average Treatment Effect that averages (with weights) over firms' causal responses of innovation outputs to small changes in R&D spending due to the IV.

[18] See Table A14 and Appendix C.5.

R&D data from CT600 and RDTC. CT600 is an administrative panel dataset provided by the HMRC Datalab, which consists of tax assessments made from the returns for all UK companies liable for corporation tax. The dataset covers financial years 2000 to 2011 and contains all information provided by firms in their annual corporate tax returns. We are specifically interested in the RDTC sub-dataset, which contains all information related to the R&D Tax Relief Scheme, including the amount of qualifying R&D expenditure for each firm-year and the scheme under which it made the claim (SME vs. Large Company Scheme). Firms made 53,000 claims over 2000-11 for a total of £5.8 billion in R&D tax relief with about 80% of the claims were under the SME Scheme.

We observe R&D when firms claim R&D tax relief. All firms performing R&D are in principle eligible for tax relief, which as we have discussed are generous. Further, all firms must submit tax returns each year and claiming tax relief is a simple part of this process. Hence, we believe we have reasonably comprehensive coverage of a firm's qualifying R&D spending.[19] Ideally, we would cross check at the firm level with R&D data from other sources, but UK accounting regulations (like the US regulation of privately listed firms) do not insist on small companies' reporting R&D. Statistics provided by HMRC indicate that qualifying R&D expenditure amounts to 70% of total business R&D (BERD).[20] In addition, the data contain information on the SME status of firms that claimed R&D tax relief. However, this information is not available for non-R&D-performing firms.

Financial data from FAME. Employment and total assets are not included in CT600 because they are not required on corporate tax forms. Furthermore, only tax-accounting sales is reported in CT600, while the SME definition is based on financial-accounting sales as reported in company accounts.[21] Consequently, we turn to a second dataset, FAME, which contains all UK company accounts since about the mid-1980's. In addition to total assets, sales, and employment, [22] FAME also provides firms' industry, location, capital investment, other expenditures, profits, remuneration, and other financial information through to 2013, although coverage quality differs greatly

[19] That is, given the ease of the process, selection into claiming R&D tax relief (conditional on having performed R&D) is unlikely a first order concern.

[20] There are various reasons for this difference, e.g., BERD includes R&D spending on capital investment whereas qualifying R&D does not (only current expenses are eligible for tax relief). It is also the case that HMRC defines R&D more narrowly for tax purposes than BERD, which is based on the Frascati definition.

[21] Tax-accounting sales turnover is calculated using the cash-based method, which focuses on actual cash receipts rather than their related sale transactions. Financial-accounting turnover is calculated using the accrual method, which records sale revenues when they are earned, regardless of whether cash from sales has been collected.

[22] Financial variables are reported in sterling while the SME thresholds are set in euros, so we convert assets and sales using the same conversion rules used by HMRC for this purpose (see Appendix B.5 for details).

across variables (depending on reporting requirement). As both CT600 and FAME cover the universe of UK firms, we obtain an excellent match rate of 95% between the two datasets (see Online Appendix B.4).

Choice of Running variable. While all firms are required to report their total assets in company accounts, reporting of sales and employment is mandatory only for larger firms. In our FAME data, over 2006-11, only 15% of firms reported sales and only 5% reported employment. By comparison, 97% reported assets. Even in our baseline sample of relatively larger firms around the SME assets threshold of €86m, sales and employment are still only available for 67% and 55% of firms respectively. Thus, to avoid the problem of selection due to missing values, we focus on the SME assets threshold and use this as the primary running variable in our baseline fuzzy RD Design in Section 3. It is worth noting that using only one threshold for identification in a multiple threshold policy design does not violate the RD Design identifying assumptions, although it may reduce the efficiency of the estimates.

We also experiment with using employment and sales to determine SME status, which yields qualitatively similar results. In principle, using additional running variables should increase efficiency, but in practice, it does not lead to material gains in the precision of the estimates. (See Online Table A16 and Appendix C.6)

Patent data from PATSTAT. Our third dataset, PATSTAT, is the largest available international patent database, which covers close to the population of all worldwide patents since the 1900s. It brings together nearly 70 million patent documents from over 60 patent offices, including all of the major offices such as the European Patent Office (EPO), the United States Patent and Trademark office (USPTO), the Japan Patent Office (JPO), and also the UK Intellectual Property Office. To assign patents to UK-based companies we use the matching algorithm between PATSTAT and FAME implemented by Bureau Van Dijk and available from the ORBIS database. Over our sample period, 94% of patents filed in the UK and 96% of patents filed at the EPO have been successfully associated with their owning company. We consider all patents filed by UK companies up to 2015. Our dataset contains comprehensive information from the patent record, including application date, citations, and technology class.

Importantly, PATSTAT includes information on patent families, each of which is a set of patents protecting the same invention across several jurisdictions. This information allows us to identify all patent applications filed worldwide by UK companies, while avoiding double-counting inventions sought to be protected in multiple jurisdictions. We thus use the number of patent families, irrespective of where the patents are filed, as our baseline measure of innovation. Each patent family is assigned to its earliest application year, which tracks R&D much more closely than publication or granted dates.

Although patents have their limitations (see Hall et al., 2013), numerous studies have demonstrated a strong link between patenting and firm performance.[23] To tackle the problem of highly heterogeneous patent values, we use various measures of patent quality, including weighing patents by the number of countries where IP protection is sought (e.g., US and Japan) or the number of future citations.[24]

4.2 Baseline sample descriptive statistics

Our baseline sample contains 5,888 firms with total assets in 2007 between €61m and €111m, based on a €25m bandwidth around the SME assets threshold of €86m, with 3,651 and 2,327 firms below and above the threshold respectively. Although our choice of bandwidth was guided by results from the Calonico, Catteneo, and Titunik's (2014) optimal bandwidth approach, we decided to have a single bandwidth for both R&D and patent outcomes in order to have a consistent baseline sample.[25] Nevertheless, we are careful to show robustness to alternative bandwidths and kernel weights.

Our key outcome variables are total R&D expenditures and the number of patents applications filed. All nominal variables are converted to 2007 prices, and all outcome variables are winsorized at 2.5% of non-zero values to mitigate the leverage of outliers.[26] In 2006-08, 259 firms in our baseline sample had positive R&D and this number rose to 329 over 2009-11, covering roughly 5% of aggregate R&D expenditure. 172 firms filed 1,127 patents over 2006-08, and 189 firms filed 1,628 patents over 2009-13. Despite the typically low shares of R&D performers and patenters in a firm population,[27] we choose to employ the full population of firms around the threshold as this provides the cleanest design to capture both intensive and extensive margin effects of the policy change.[28] For similar reason, firms that exited after 2008 are kept in the sample to avoid selection

[23] E.g., see Hall, Jaffe, and Trajtenberg (2005) on US firms, or Blundell, Griffith, and Van Reenen (1999) on UK firms.

[24] Variations of these quality measures have been used by Lanjouw et al. (1998), Harhoff et al. (2003), and Hall et al. (2005), among others.

[25] The Calonico, Catteneo, and Titunik's (2014) optimal bandwidth for using R&D as the outcome variable is €20m, and for using patents as the outcome variable is €31m (see Tables A4, A5, and Appendix C.4). Our baseline bandwidth choice of €25m is in between these two.

[26] This is equivalent to winsorizing the R&D of the top 5 to 6 R&D spenders and the number of patents of the top 2 to 4 patenters in the baseline sample each year. We also show robustness to excluding outliers instead of winsorizing outcome variables, and to using raw R&D and patent data as outcome variables.

[27] The shares of R&D performers and patenters among the universe of UK firms during 2009-11 are 0.9% and 0.4% respectively (Table B1), much lower than the corresponding shares in our baseline sample.

[28] Given that our variations come from a small subset of firms, one concern is that using the much larger full-population baseline sample could create artificial statistical power. However, conditioning on more relevant subsets of firms (e.g., pre-policy R&D performers or patenters) yields qualitatively similar results with comparable statistical significance.

bias (as firm survival is also a potential outcome) and are given zero R&D and patents.

Table 1 provides some descriptive statistics on the baseline sample. Over 2006-08, firms below the threshold spent on average £61,030 per annum on R&D and firms above the threshold £93,788. After the policy change, over 2009-11, these numbers became £80,269 and £101,917. That is, the gap in R&D spending between the two groups reduced by more than 30% from £32,758 pre-policy to £21,649 post-policy. In terms of innovation outputs, the average number of patents per annum was similar between the two groups before the policy change (0.061 vs. 0.067), while post-policy, over 2009-13, firms below the SME assets threshold filed around 40% more patents than those above the threshold (0.063 vs. 0.044).

These "difference-in-differences" (D-in-D) estimates are consistent with our hypothesis that the 2008 policy change induced firms newly eligible for the SME Scheme to increase their R&D and patents. The naïve D-in-D estimates imply increases of 15% in R&D and 38% in patents from being below the new SME assets threshold. However, differential time effects across firms of different size would confound these simple comparisons. In particular, recessions are likely to have larger negative effects on smaller firms (which are less likely to survive and are harder hit by credit crunch) than larger firms, which would lead to an underestimate of the positive causal impact of the policy. This is a particular concern in our context as the 2008-09 global financial crisis coincided with the policy change. Even the addition of trends will not resolve the issue because the Great Recession was an unexpected break in trend. However, the RD Design is robust to this problem, as it enables us to assume that the impact of the recession is similar around the threshold.

Balance of predetermined covariates. Table 2, which reports the balance of predetermined covariates conditional on the running variable, shows that firms right below and above the threshold are indeed similar to one another in their observable characteristics prior to the policy change. The differences in sales, employment, capital, and value added between these two groups of firms in 2006 and 2007 are both small and statistically insignificant. The same is true for R&D spending and the number of patents filed (as discussed in detail in the next section), as well as other measures of firm performance (e.g., investments, profit margins, productivity). Consequently, we now turn to implementing the RD Design of equations (1)-(3) directly to investigate the casual effects of the 2008 policy change.

5. Evidence of R&D tax relief's effects on R&D and patents

5.1 Evidence of effect on R&D

Table 3 examines the impact of the policy change on R&D (equation 1) over time among firms in the baseline sample (subsection 4.2). In columns 1-3, we find no statistically significant discontinuity in R&D at the SME assets threshold in the pre-policy years 2006 and 2007 or the transition year 2008. On the other hand, from 2009 onward, firms just below the threshold had significantly more R&D than firms just above the threshold (columns 4-6). Columns 7 and 8 average the three pre-policy/transition and three post-policy years respectively, and column 9 uses the difference between these averages as outcome variable. Although formally our analysis indicates no pre-policy trends, we consider column 9's a conservative estimate (£60,400), especially given the positive sign of the coefficient in columns 1-3. Similarly, column 10 directly controls for pre-policy R&D, which yields a near identical estimate of £63,400, statistically significant at the 5% level. Given that our instrument $E_{i,2007}$ does not perfectly predict a firm's SME status, these reduced-form coefficients present a lower bound for the effect that the SME Scheme had on R&D. Even then, they are not far below the pre-policy average annual R&D of £74,000, suggesting that the policy's economic impact was substantial.[29] In subsection 7.2, we discuss in detail how we are able derive the true magnitude of the policy's effect even when we cannot observe SME status for the full baseline sample.

Figure 2 shows the visible discontinuity in post-policy R&D at the SME assets threshold.[30] While larger firms unsurprisingly do more R&D as shown by the upward sloping regression lines, right across the threshold there exists a sharp downward jump that is consistent with a policy effect. To examine if this jump is unique to the €86m threshold, we run a series of placebo tests at all possible integer thresholds between €71m and €101m using the same specification and €25m sample bandwidth. Online Figure A5 shows that the estimated discontinuity in post-policy R&D peaks at €86m and is not statistically different from zero almost anywhere else.[31] That is, the jump exists only at the true SME threshold, as a result of the 2008 policy change. Finally, our results are robust to a wide range of alternative specifications (Online Table A4) as discussed in detail in Online Appendix C.4.[32]

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[29] Relatedly, it is worth noting that the equivalent reduced-form estimates for both R&D and patent outcomes are even larger among firms with fewer than 500 employees in 2007 (for which the assets criterion was binding), while they are not statistically significant otherwise (see Table A3 and Appendix C.2).

[30] Unlike Figure 1, which displays firms', publicly available financial data, Figures 2 reveals confidential information regarding firms' R&D and therefore is subject to HMRC's strict disclosure rules, including restriction on the minimum number of firms per bin, which results in large bin size.

[31] In fact, *all* placebo-threshold estimates are not statistically different from zero when we truncate the corresponding estimation samples at the true threshold so as to avoid contamination (see Online Appendix C.3 for further details).

[32] These robustness tests include (i) adding higher polynomial controls, (ii) employing alternative sample bandwidths and kernel weights, (iii) using different winsorization or trimming rules, (iv) adding industry and/or location fixed effects, (v) implementing Calonico, Catteneo, and Titunik's (2014) robust bias-corrected optimal bandwidth RD Design, and (v) employing count data models (Poisson and Negative Binomial) instead of OLS..

5.2 Evidence of effect on patents

Turning to our key outcome of interest, Table 4 reports the impact of the policy change on patents (equation 2) using the same RD specification and sample as Table 3. As with R&D, columns 1-3 show no significant discontinuity around the threshold in patenting activity prior to the policy change. By contrast, there was a significant increase in patenting in the post-policy period from 2009 onward, which persisted through to the end of our patent data in 2015, 7 years after the policy change (Panel A, columns 4-10). Although we will focus on the 5 years from 2009 to 2013 (Panel B, columns 5-7) as our baseline "post-policy period" for subsequent patent analyses, all results are qualitatively similar if we use the 2009-11 (Panel B, columns 2-4) or 2009-15 (Panel B, columns 8-10) averages instead. Column 5 of Panel B reports a discontinuity estimate of 0.069 extra patents per year for firms below the SME assets threshold compared with firms above the threshold (as shown in Figure 3), while the corresponding coefficient for the pre-policy period is less than half the size and statistically insignificant (Panel A, column 1). If we use the more-conservative before-after or lagged-dependent variable-specifications, the discontinuity estimates are 0.042 and 0.049 (Panel A, columns 6 and 7). As with R&D, these coefficients present a lower bound for the effect that the SME Scheme had on patents, and they are sizeable in comparison with the pre-policy mean patents of 0.064.

The patents effect is one of our key results. Note that the R&D Tax Relief Scheme does not require a firm to show any patenting activity, in either filing for R&D tax relief by the firm or auditing by the tax authority of how the R&D is spent. Therefore, there is no administrative pressure to increase patenting. We observe a response in patenting as soon as 2009 as patent *applications* are often timed quite closely to research expenditures.[33] It is also possible that firms filed their off-the-shelf inventions when the policy change effectively reduced their patent filing costs. This would translate into a larger estimate in 2009 but could not explain the persistent effects through 2015.[34] Online Figure A6 and Table A5 show that these results are robust to a wide range of placebo and robustness tests.

Considering patent quality. As patents vary widely in quality, one important concern is that

[33] See the literature starting with Hall, Griliches and Hausman (1986) that consistently finds the strongest link between contemporaneous R&D expenditure and patenting when exploring a lag structure of at the firm level (Gurmu and Pérez-Sebastián, 2008, Wang et al, 1998, Guo and Trivedi, 2002). Wang and Hagedoorn (2014) offer evidence for the following explanation: firms typically will start to apply for some patents very early on in a longer R&D process. This then followed by further R&D spending and subsequent patents that provide improvements and further refinements on the initial patent.

[34] However, as SMEs grew into large companies, resulting in 2007 assets' becoming a weaker predictor of firm's SME status (Table 9), the corresponding reduced-form estimates also decrease in magnitude overtime. Indeed, we find evidence of substantial policy-induced increase in employment that is consistent with this interpretation (Table A15).

the additional patents induced by the policy could be of lower value. Table 5 thus considers different ways to account for patent quality. Column 1 reproduces our baseline patent-count result. Column 2 counts only patents filed at the UK patent office, column 3 the European Patent Office (EPO), and column 4 the USPTO. Since filing at the EPO and USPTO is more expensive than just at the local UK office,[35] these patents are likely of higher value. It is clear that the policy also had a positive and significant effect on these high value patents. Although the coefficient is larger for UK patents, so is the pre-policy mean. In fact, the policy's "proportional effects" (the RD coefficient divided by the pre-policy mean of the dependent variable, reported in the final row) on EPO and USPTO patents are no smaller than that on UK patents (1.2 for EPO, 1.6 for USPTO, and 1.0 for UK patents). Relatedly, column 5 weighs patents by patent family size, i.e., the total number of jurisdictions in which each invention is patented, which generates a comparable proportional effect of around 0.9.

Column 6 weighs patents by future citations, yielding a positive and significant estimate.[36] However, as our data is very recent for citation count purpose, looking at the proportional effect on citation-weighted patents is less meaningful.[37] Instead, we consider the number of patents that are in the top citation quartile (with respect to their technology class-by-filing year cohorts) in column 7, which produces a proportional effect of 1.0 similar to the baseline. Finally, we examine heterogeneity by technology segment, looking specifically at chemicals (including biotechnologies and pharmaceuticals) in column 8 and information and communication technologies (ICT) in column 10. These sectors did enjoy larger proportional effects (both around 1.7), but columns 9 and 10 show that our results are not all driven by these technologically dynamic sectors.

We further examine various other indicators of patent quality in Online Table A8, such as technological scope, generality index, or originality index, all of which yield qualitatively similar results. That is, there is no evidence from Tables 5 and A7 of any major fall in innovation quality due to the risk that the policy induces only low value innovation. Instead, the policy appears to robustly raise both patent and quality-adjusted patent counts (but not necessarily average patent quality) across many different measures of patent quality.

[35] For example, filing at the EPO costs around €30,000 whereas filing just in the UK costs between €4,000 and €6,000 (Roland Berger, 2005).

[36] We focus on citation-weighted patent counts instead of average citations per patents, as the latter is not defined for the majority of non-patenting firms. Furthermore, we do not expect the policy to increase average patent quality, but quality-adjusted patent counts (i.e., the policy did induce meaningful patents/innovations of some value).

[37] As pre-policy patents had more time to accumulate citations relative to post-policy ones, the proportional effect on citation-weighted patents is expectedly lower. This issue also extends to patent family counts (pre-policy patents had more time to be filed in more jurisdictions), which explains the also lower proportional effect in column 5.

5.3 Returns to R&D for the knowledge production function

Table 6 estimates knowledge production functions (patent IV regressions) where the key right-hand-side variable, R&D, is instrumented by the discontinuity at the SME threshold (equation 3). The corresponding first-stage and reduced-form regressions were reported in Tables 3 and 4 respectively. As discussed in Section 3, the exclusion restriction, which requires that the instrument effects innovations only through qualifying R&D, likely holds in our setting given the lack of evidence of policy effects on non-qualifying expense categories (see Online Table A14 and Appendix C.5). Column 1 presents the OLS specification, which as expected reports a positive association between patents and R&D. Column 2 reports a larger IV coefficient, implying that one additional patent cost on average \$2.4 million (= 1/0.563 using a \$/£ exchange rate of 1.33) in additional R&D. Unlike β^{R} and β^{PAT}, this IV estimate is not subject to the fuzziness of our RD Design but instead captures the true marginal effect of policy-induced R&D on patents. At the pre-policy means of R&D and patents of £0.074m and 0.064 respectively, it implies an elasticity of patents with respect to R&D of 0.65 (= (0.563/0.064)/(1/0.074)) for our IV estimates (compared with 0.24 for OLS). If we also control for average pre-policy patents over 2006-08, the IV estimate decreases from 0.56 to 0.43 (Panel B of Online Table A6), implying an elasticity of 0.50.

The next columns of Table 6 compare UK, EPO, and US filings. All indicate significant effects of additional R&D on patents, which are again larger for IV than OLS. The corresponding costs for one additional UK, EPO, or USPTO patent were \$2.1, \$4.5, and \$4.0 million respectively (columns 4, 6, and 8), which are broadly in line with the existing estimates for R&D costs per patent of \$1 to \$5 million.[38] Despite the weak adjusted first-stage F-statistic of 5.6, the Anderson-Rubin weak-instrument-robust inference tests indicate that all of the IV estimates are statistically different from zero even in the possible case of weak IV. As with R&D and patent results, these IV estimates are robust to wide range of alternative specifications, as reported in Table A6.

The fact that the IV estimates are larger than OLS ones is consistent with the LATE interpretation, which implies that the IV specification estimates the impact of additionally induced R&D on patents among complier firms (i.e., those increased their R&D because of the policy). These firms were more likely to be financially constrained, thus also more likely to have higher-return R&D projects which they could not have taken without the policy. Table 7 presents some direct evidence supporting this hypothesis. We construct an industry-level measure of financial constraints as the average cash holdings to capital ratio in each three-digit SIC industry among the

[38] See Hall and Ziedonis (2001), Arora, Ceccagnoli, and Cohen (2008), Gurmu and Pérez-Sebastián (2008), and Dernis et al. (2015).

population of UK firms (see Online Appendix B.5 for details). All else equal, we expect industries with higher cash-to-capital ratios to be less financially constrained. In columns 1 and 4 of Table 7, we fully interact all right-hand-side variables in our baseline specification with this industry cash-to-capital measure. The interaction terms indicate that the policy (reduced-form) effects on both R&D and patents were significantly larger for firms in financially constrained sectors. The other columns split the baseline sample into industries below and above median in level of financial constraints. The results again indicate that the policy had positive and significant effects only on likely-financially-constrained firms. Columns 2 and 5 further report that the estimated returns to R&D on patents in financially constrained sectors is 0.602 (significant at the 5% level), larger than the baseline IV estimate of 0.563. This is consistent with our hypothesis that the returns to R&D are higher among more financially constrained firms. We also calculate the Rajan and Zingales (1998) index of industry external-finance dependence and find qualitatively similar results (Online Table A13).

6. R&D technology spillovers on patents

The main economic rationale given for more generous tax treatment of R&D is that there are technological externalities, so the social returns to R&D exceed the private returns. Our design also allows us to estimate the causal impact of tax policies on R&D spillovers, i.e., innovation activities of firms that are *technologically connected* to policy-affected firms, through employing a similar RD specification with connected firms' patents as the outcome variable of interest.[39] To our knowledge, this paper is the first to provide Regression Discontinuity estimates of technology spillovers.

Spillover estimation framework. We start from a general system of spillover equations in which each firm's innovation output (patents) depends on (i) its own R&D, (ii) all connected firms' R&D, and (iii) all connected firms' innovation outputs (see Carneiro et al, 2020 and Manski, 1993, for similar set-ups). Online Appendix D.1 shows that given this structure, an increase in firm *i*'s R&D can affect a connected firm *j*'s patenting via both a *direct* spillover from firm *i*'s R&D, and an *indirect* spillover from firm *i*'s patenting, which increases with firm *i*'s R&D. The *net* effect of these two spillover channels can be recovered from the IV specification:

$$PAT_j = \alpha_{4,t} + \xi R_i + f_4(z_{i,2007}) + g_4(z_{j,2007}) + \varepsilon_{4ij}, \quad (4)$$

[39] See Dahl, Løcken, and Mogstad, 2014, for a similar methodological approach in a different context.

In equation (4) each observation is a dyad of connected firms *i-j*, and firm i's R&D (R_i) is instrumented with its below-assets-threshold indicator ($E_{i,2007}$) as in equation (3).[40] The exclusion restriction requires that $E_{i,2007}$ only affects PAT_j through spillovers from R_i, and can be decomposed into two elements. First, $E_{i,2007}$ should only affect firm j's innovation activities (and thus, PAT_j) via firm *i*'s innovation activities; and second, $E_{i,2007}$ should only affect firm *i*'s innovation activities (including R_i and PAT_i) via R_i (equation 3's exclusion restriction, as discussed in Section 3). Since $E_{i,2007}$ is as good as random in the RD Design, under mild sufficiency conditions, it is also conditionally uncorrelated with connected firm j's characteristics, including the firm's eligibility for the SME Scheme (see Online Appendix D.2). This suggests that the first element of the exclusion restriction is also satisfied. Equation (4) then produces consistent estimates of the magnitude of R_i's *net* spillovers on PAT_j.

In addition, we also consider the reduced-form corresponding to equation (4):

$$PAT_j = \alpha_5 + \theta E_{i,2007} + f_5(z_{i,2007}) + g_5(z_{j,2007}) + \varepsilon_{5ij}, \tag{5}$$

This estimates the impact of firm *i*'s likelihood of eligibility for the SME Scheme on connected firm *j*'s innovation output. Similar to β^R and β^{PAT} (equations 1 and 2), θ gives a lower bound for the spillovers that the SME Scheme had on firms connected to the scheme's recipients.

Technologically connected firms. We consider two firms to be technologically connected if (i) most of their patents are in the same three-digit IPC technology class and (ii) the Jaffe (1986) technological proximity between them is above median (0.75).[41] The first criterion allows us to allocate each dyad to a single technology class, whose size, as we will show later, determines the strength of the spillovers. However, as two firms sharing the same primary technology class could still have very different patent portfolios, we refine the definition of technological connectedness with the second criterion. Relaxing either criterion, or imposing further restrictions, does not materially affect our qualitative findings (see Online Appendices D.3 and D.5).

Our spillover estimation sample consists of all firm *i* and *j* dyads ($i \neq j$) such that firm *i* is within our baseline sample of firms with total assets in 2007 between €61m and €111, and firm *j* is technologically connected to firm *i.* Firms *i* and *j* are drawn from the universe of UK patenting firms over 2000-08 for which we can construct these measures. Similar to Table 6, we measure PAT_j as firm *j*'s average patents over 2009-13 and R_i as firm *i*'s average R&D over 2009-11.

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[40] $f_4(z_{i,2007})$ and $g_4(z_{j,2007})$ are polynomials of firms *i* and *j*'s total assets in 2007.

[41] The Jaffe technological proximity equals 1 if firms i and j have identical patent technology class distribution and 0 if the firms patent in entirely different technology classes (see Appendix D.3 for details).

Discussion of results. Column 1 of Table 8 reports the reduced-form spillover regression (equation 5) using the full dyadic sample, which yields a small and statistically insignificant policy spillover coefficient, θ. However, we expect spillovers to be measurable only in small-enough technology classes, where a single firm has better chances of influencing the field's technological frontier and thereby other firms' innovations (see Online Appendix D.1).[42] Indeed, column 2 shows that the coefficient of the interaction term between $E_{i,2007}$ and the size of the dyad's technology class is negative and statistically significant, consistent with our hypothesis. We also semi-parametrically estimate θ as a function of the technology class's size percentile (see Online Appendix D.4 for details), which again results in a downward sloping curve as plotted in Figure 4.

Guided by Figures 4 and A9, we split the full sample of all connected firm dyads by their technology class size at 200 firms, which is the 40th percentile. The reduced-form policy spillover coefficient in this subsample (column 4 of Table 8) is positive and significant. More notably, it is an order of magnitude larger than that in larger technology classes (column 3). These results indicate the presence of positive spillovers from the R&D tax policy and are robust to a range of robustness tests (see Appendix D.5).[43] The last two columns implement the IV specification (equation 4) using the full dyadic sample (column 7) and the subsample of small technology classes (column 8). The corresponding first stage estimates (reported in columns 5 and 6) show there is no problem of weak instruments. Consistent with the reduced-form results, among connected firms in small technology classes, the R&D spillover estimate is statistically significant at the 5% level by both the conventional Wald test and the Anderson-Rubin weak instrument-robust inference test. In terms of magnitude, this spillover estimate is about 40% (= 0.22/0.56) of the own effect of policy-induced R&D on own patents (see column 2 of Table 6).

Direct versus indirect spillovers. As noted above, Table 8's IV estimates capture the *net* spillovers of firm i's R&D on connected firm j's patents, which on its own is an important policy-relevant parameter. Furthermore, Online Appendix D.1 shows that for a given value of the effect of PAT_i on PAT_j (namely π), it is possible to back out the *direct* effects of R_i and R_j on PAT_j (ψ and κ respectively) from the IV estimates of the *net* R&D spillover effect (equation 4's ξ) and *net* own R&D effect (equation 3's γ). As plotted in Online Figure A7, both ψ and κ are positive for any reasonable value of π (i.e., π smaller than 0.98). That is, it is highly likely that R&D also has

[42] For the same reason, Angrist (2014) recommends and Dahl, Løcken, and Mogstad (2014) implements looking at groups with small numbers of peers when examining spillover effects.
[43] These tests include (i) employing alternative clustering schemes, (ii) including different polynomial controls for $z_{i,2007}$, $z_{j,2007}$, $E_{j,2007}$, and pre-policy patents, (iii) using alternative definitions of technological connectedness, and (iv) considering alternative post-policy (as well as pre-policy) periods.

positive *direct* (not just net) impact on connected firms' innovations. Finally, Appendix D.6 implements Bloom, Schankerman and Van Reenen's (2013) methodology to estimate both knowledge spillover and business stealing effects of rival R&D competition. The results also suggest that policy-induced R&D has sizable positive impacts on innovation outputs of not only firms directly receiving R&D tax relief but also other firms in similar technology areas.

7. Magnitude of effects and economic implications

7.1 Intensive versus extensive margins

In Online Table A9, we estimate the RD specification in equations (1) and (2) with indicators of positive R&D or patents as outcome variables and find evidence of extensive margin effect on patents, but not R&D. Alternatively, we split the baseline sample by firms' pre-policy R&D and patents in Online Table A10, and by industry pre-policy patenting intensity in Online Table A11. Both exercises show that firms and sectors already engaged in innovation activities had the strongest responses to the policy change. These results provide strong evidence that more generous R&D tax relief did not materially affect a firm's selection into R&D performance but worked mostly through the intensive margin. That is, the policy appears to mostly benefit firms that were already performing R&D and filing patents before the policy change, thereby increased these firms' chances of continuing to have patented innovations in post policy change.

We also split the baseline sample by whether firms made some capital investments in the pre-policy period (Online Table A12). The results suggest that policy effects on R&D and patents were larger among firms that had invested, suggesting that current R&D and past capital investments are more likely complements than substitutes. This is consistent with the idea that firms having previously made R&D capital investments have lower adjustment costs and therefore respond more to R&D tax incentives (Agrawal, Rosell, and Simcoe, 2020).

7.2 Magnitude of effects and tax-price elasticities

What is the implied elasticity of R&D with respect to its tax-adjusted user cost (e.g., Hall and Jorgenson, 1967, or Bloom, Griffith, and Van Reenen, 2002)? Given the large policy-induced R&D increase in our setting, we focus on the following arc elasticity measure, which calculates the percentage difference relative to the midpoint instead of either end points:[44]

[44] Alternatively defining the elasticity as the log difference in R&D capital over the log difference in the tax-adjusted user cost of R&D, i.e., $\eta = \frac{\ln(R_{SME}/R_{LCO})}{\ln(\rho_{SME}/\rho_{LCO})}$, yields quantitatively similar elasticity estimates (Tables A18 and A19).

$$\eta_{R,\rho} = \frac{\%\text{ difference in } R}{\%\text{ difference in } \rho} = \frac{\frac{R_{SME} - R_{LCO}}{(R_{SME} + R_{LCO})/2}}{\frac{\rho_{SME} - \rho_{LCO}}{(\rho_{SME} + \rho_{LCO})/2}}$$

where ρ_{SME} and ρ_{LCO} are the firm's tax-adjusted user cost of R&D under the SME and the Large Company ("LCO") Schemes, and R_{SME} and R_{LCO} are the firm's corresponding R&D.[45]

Deriving the percentage difference in R. As mentioned in Sections 3 and 5, to obtain estimates of the treatment effects of the SME Scheme on R&D (i.e., $R_{SME} - R_{LCO}$) and patents, we need to scale equations (1) and (2)'s β^R and β^{PAT} by how sharp $E_{i,2007}$ is as an instrument for actual eligibility $SME_{i,t}$. We estimate this "sharpness" λ using the following equation:

$$SME_{i,t} = \alpha_{6,t} + \lambda_t E_{i,2007} + f_{6,t}(z_{i,2007}) + \varepsilon_{6i,t} \quad (6)$$

Equations (1) and (6) correspond to the first stage and reduced form equations in a fuzzy RD Design that identifies the effect of the more generous SME Scheme on a firm's R&D at the SME assets threshold, using $E_{i,2007}$ as an instrument for $SME_{i,t}$.

Our setting differs from standard fuzzy RD Designs in that $SME_{i,t}$ is missing for the firms with zero R&D. Therefore, we can only estimate equation (6) on the subsample of R&D performing firms.[46] Selection into this subsample by R&D performance raises the concern of whether the resulting $\widehat{\lambda}$ is a consistent estimator of the true λ in the full baseline sample, which includes non-R&D performers. In Online Appendix A.4 we prove that a sufficient condition for $E(\widehat{\lambda}) = \lambda$ is that the SME Scheme does not increase firm's likelihood of performing R&D, which holds in our setting as discussed in subsection 7.1. Then the composition of eligible and non-eligible firms below and above the threshold in the R&D-performer subsample would be the same as that in the full baseline sample. As a result, we are able to derive $\frac{\widehat{\beta}^R}{\widehat{\lambda}}$ and $\frac{\widehat{\beta}^{PAT}}{\widehat{\lambda}}$, in which $\hat{\beta}$'s are estimated using the full baseline sample and $\hat{\lambda}$ the R&D-performer subsample, as consistent estimators of the causal effect of the SME Scheme on R&D and patents at the eligibility threshold. We can also retrieve these estimators' empirical distributions and confidence intervals using bootstrap.

Table 9 reports the results from estimating equation (6) using the subsample of R&D performing firms in each respective year. Columns 1-3 show that being under the new SME assets threshold in 2007 significantly increases the firm's chance of being eligible for the SME Scheme in the

[45] Formally, the numerator of the tax price elasticity should be the R&D capital stock rather than flow expenditure. However, in steady state the R&D flow will be equal to R&D stock multiplied by the depreciation rate. Since the depreciation rate is the same for large and small firms around the discontinuity, it cancels out (see Appendix E.1).

[46] For the same reason, we cannot directly estimate the corresponding structural equation for the full baseline sample.

post-policy years, even though the instrument's sharpness expectedly decreases over time. Columns 4-6 aggregate a firm's SME status over different post-policy periods, which yield coefficients in the range of 0.25 to 0.46 that are all significant at the 1% level. In what follows we will use the mid-range coefficient of 0.353 (column 5) as the baseline estimate of λ.[47] Combined with $\hat{\beta}^R$ = £60,400 (column 9 of Table 3), this implies a causal treatment effect (of the more generous SME Scheme) of £60,400/0.353 = £171,200 and a percentage difference in R&D of 1.07.[48]

Deriving percentage difference in ρ. In Online Appendix E.3, we explain in detail how we calculate the tax-adjusted user cost ρ_f for $f \in \{SME, LCO\}$ based on the actual design of the R&D Tax Relief Scheme. The resulting average tax-adjusted user cost of R&D is 0.15 under the SME Scheme and 0.19 under the Large Company Scheme over 2009-11, which translates into a percentage difference in user cost of 0.27.

Deriving $\boldsymbol{\eta_{R,\rho}}$. Putting the elements together we obtain a tax-price elasticity of R&D of about 4 (= 1.07/0.27), or alternatively 3.3 if we estimate both β^R and λ using the subsample of R&D performers (row 7 of Online Table A18). Analogous calculations yield an elasticity of patents with respect to R&D user cost of 3.6 (see Online Appendix E.4). These elasticity estimates are substantially higher than the typical values between one and two found in other studies. However, Acemoglu and Linn (2004) also find R&D elasticity estimates in the range of 4 with respect to market size and suggest that this should be the same as R&D elasticity with respected to its user cost. Similarly, Akcigit et al. (2018) find an elasticity of 3.5 using state level variation in income tax rules. In addition, based on the bootstrapped distribution of $\hat{\eta}_{R,\rho}$ (reported in detail in Panel A of Online Table A19), a left-sided 5%-sized test rejects the hypothesis that R&D tax-price elasticity lower than 1.1.

It is worth highlighting that our setting is different from those in previous studies on R&D tax credits, which have explicitly (by using Compustat) or implicitly (by using aggregate data) focused on larger firms, as R&D is concentrated in such entities. Our sample, by contrast, is predominantly smaller firms around the €86m threshold. As we have argued in subsection 5.3, these firms are more likely to be financially constrained and thus more responsive to R&D tax incentives. Many

[47] A firm's SME status over a period is the maximum of its SME status in each of the year within the period. We also report elasticity estimates derived from alternative estimates of λ (using different post-policy periods) in Table A18.

[48] That is, $\frac{R_{SME}-R_{LCO}}{(R_{SME}+R_{LCO})/2} = \frac{171.2}{(171.2+74.0+74.0)/2} = 1.07$. As the tax-adjusted user cost of R&D for large companies remains unchanged over 2006-11 (Table A2), it seems reasonable to use the average R&D over 2006-08 as a proxy for how much an average firm would spend on R&D if it remained a large company over 2009-11.

recent empirical studies find greater responses of smaller firms to business support policies (see Criscuolo, 2019 and the survey there). In particular, we showed that the treatment effect was much larger for firms that are likely to be financially constrained (Table 7).[49] Finally, note that the policy change was introduced during the Global Financial Crisis when *all* firms were more likely to be credit constrained. Although this is not an identification threat to the RD Design, it may limit our results' external validity. However, we find that the effects of tax relief on R&D and patents were still strong as late as 2011 and 2015, well after the end of the credit crunch.

7.3 Cost effectiveness of the R&D Tax Relief Scheme

A full welfare analysis of the R&D policy is complex as one needs to take into account general equilibrium effects through spillovers (Section 6) and possibly aggregate effects on scientists' wages (Goolsbee, 1998). We take one step in this direction by implementing a simple "value for money" calculation based on how much additional R&D is generated per pound sterling of tax-payer money ("Exchequer costs"). We present details of the calculations in Online Appendix F. Our elasticity estimates imply that over 2006-11, the ratio of policy-induced R&D to tax payer costs of the SME deductible scheme is 3.9, SME payable scheme is 2.9, and Large Company Scheme is 1.5 (Online Table A20).[50] During this period, annually, £302m (£660m) of Exchequer costs generated £991m (£992m) additional R&D in the SME Scheme (Large Company Scheme). This translates into an aggregate "value for money" ratio of about 2.1.

Figure 5 shows estimates of the counterfactual business R&D (BERD) to GDP ratio in the absence of the R&D Tax Relief Scheme. It is striking that since the early 1980's UK BERD became an increasingly small share of GDP, whereas it generally rose in other major economies. Our analysis suggests that this decline would have continued were it not for the introduction and extension of a more generous fiscal regime in the 2000's. Business R&D would have been 13% lower over the 2006-11 period.

A full welfare analysis could produce even larger benefit to cost ratios. First, since the taxpayer costs are transfers, only the deadweight cost of tax should be considered (e.g., Gruber, 2011, uses 40%). Second, the additional R&D has technology spillovers to other firms as shown in Section 6. On the other hand, there may be general equilibrium effects raising the wages of R&D scientists which would dampen the overall effect.

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[49] On the other hand, the user cost elasticity among financially *unconstrained* firms is 1.3 (row 9 of Table A18), similar to the existing literature that has focused on larger firms, such as those in Compustat.

[50] For the SMEs (under either deductible or payable scheme), we use the median elasticity estimate of 4.0 in our calculations. For the large companies, we use the lower-bound elasticity estimate of 1.1.

7.4 R&D tax relief's effects on other aspects of firm performance

We examine if R&D tax relief generated impacts on other aspects of firm performance through to 2013 (Online Table A15). We again use Section 3's reduced-form RD specification but with (i) sales, (ii) employment, (iii) capital, and (iv) Total Factor Productivity (TFP) as the outcome variables. Panel B reports sizable, robust, and growing lower-bound estimates of the impact of the SME Scheme on employment over 2009-13, consistent with a dynamic in which firms increased R&D, then innovated, and then grew larger. In Panel A, the estimates are less precise but exhibit similar pattern, suggesting that the SME Scheme also had some positive impact on sales. On the other hand, we find little evidence of policy-induced increase in capital (Panel C). This may reflect contemporaneous substitution towards intangible capital (R&D) and away from tangible capital. In Panel D, we examine if more innovations translated into higher productivity by estimating the policy impact on TFP (Online Appendix B.5 has details). Similar to Panel A, the resulting coefficients, although noisy, are substantially larger in the post-policy years, especially in comparison to the pre-policy ones of close to zero. Finally, we find no effect on firm's survival after the policy change.

These results should be interpreted with caution. As discussed above, there are many missing values for employment and sales as UK accounting regulations do not insist on these being reported for smaller and medium sized enterprises (as in the US). Nevertheless, the results suggest that the policy positively affected other measures of size and productivity as well as innovation.

8. Conclusion

Fiscal incentives for R&D have become an increasingly popular policy of supporting innovation across the world. However, little is known about whether these costly tax breaks causally raise innovation for the firms receiving the subsidies, still less whether they generate spillovers on their technological neighbors. We address these issues by exploiting a change in the UK R&D Tax Relief Scheme in 2008, which raised the size threshold determining whether a firm was eligible for the more generous SME Scheme. This enables us to implement an RD Design to assess the impact of the policy on R&D and patenting. Using total assets in the pre-policy year of 2007 as the running variable, we show that there is no evidence of discontinuities around the new SME assets threshold prior to the policy change, which is unsurprising as this new threshold was used only by the R&D Tax Relief Scheme and not other programs targeting SMEs.

The policy generated economically and statistically significant increases in R&D and quality-adjusted patenting. Furthermore, the tax relief also appears to stimulate positive technology spillovers. These results suggest that R&D tax policies are effective in increasing innovation, and not simply devices for relabeling existing spending or shifting innovation activities between firms. The implied elasticities of R&D and patents with respect to changes in R&D user cost are large, probably because we focus on firms that are smaller, which have been shown to be more likely to be financially constrained than those conventionally studied in the extant literature.

There are many caveats when moving from these results to policy. Although the results are optimistic about the efficacy of tax incentives, the large effects come from smaller firms and should not be generalized across the entire firm size distribution. Yet this does imply that targeting R&D policy on financially constrained SMEs is worthwhile (although a first best policy would be to deal directly with credit market imperfections). Furthermore, our estimates are based on the period after the global financial crisis when credit frictions might have been particularly acute. However, the fact that the impact is also large seven years after the crisis suggests that the caveats should not be overstated.

We have partially examined equilibrium effects by demonstrating that the R&D Tax Relief Scheme not only stimulated innovations by firms that directly benefited, but also generated positive spillovers on other firms. However, there may be other equilibrium effects that reduce innovation. For example, subsidies are captured in the form of higher wages rather than higher volume of R&D, especially in the short-run. We believe that this is less likely a first order problem when there is large international mobility of inventors, as is the case in the UK (e.g., Akcigit, Baslandze, and Stantcheva, 2017, Moretti and Wilson, 2017). Furthermore, the policy's strong effect on patenting implies that the increase in R&D is driven by volume and not just wages. Nevertheless, investigating the magnitude of these equilibrium effects is an important area for future work.

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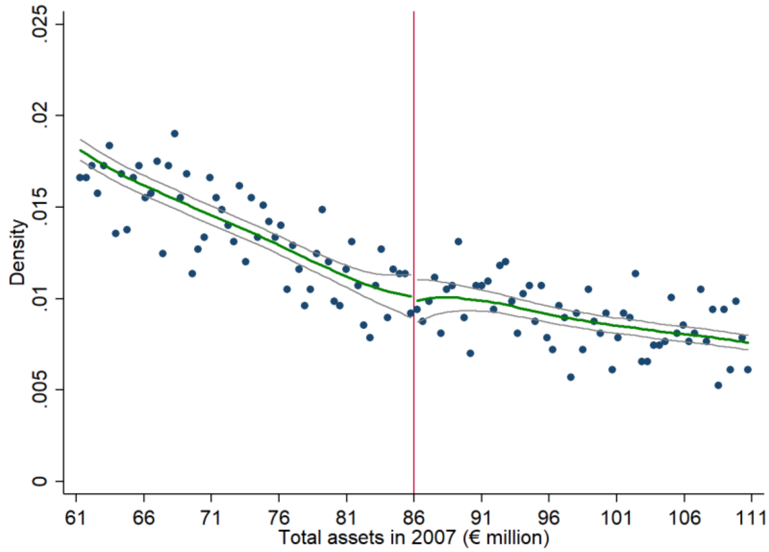
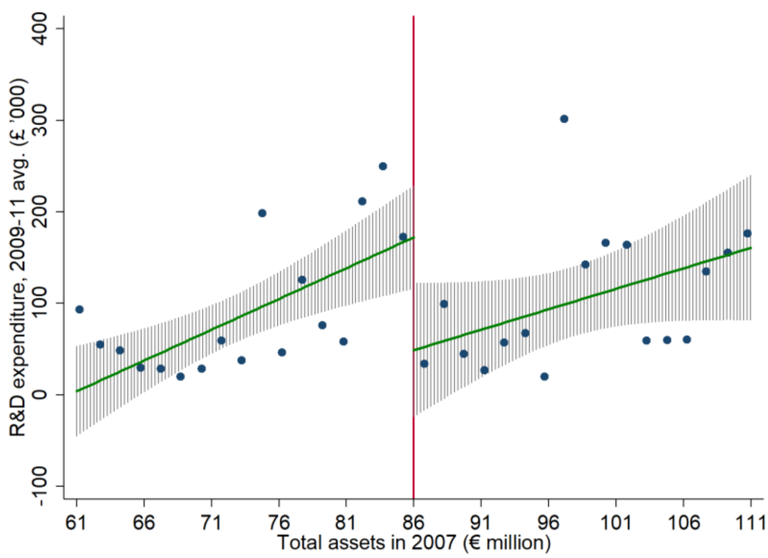
Figure 1. McCrary test for no manipulation at the SME assets threshold in 2007



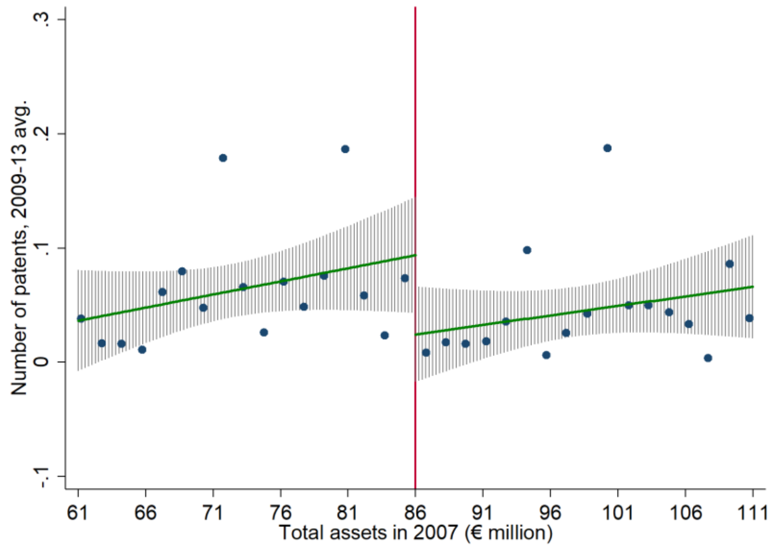
Note: This figure reports the McCrary test for discontinuity in distribution density of total assets in 2007 at the 2008 new SME assets threshold of €86m. Estimation sample includes firms with total assets in 2007 between €46m and €126m. The discontinuity estimate (log difference in density height at the SME threshold) (standard error) is -0.026 (0.088), not statistically different from zero.

Figure 2. Discontinuity in average R&D expenditure over 2009-11



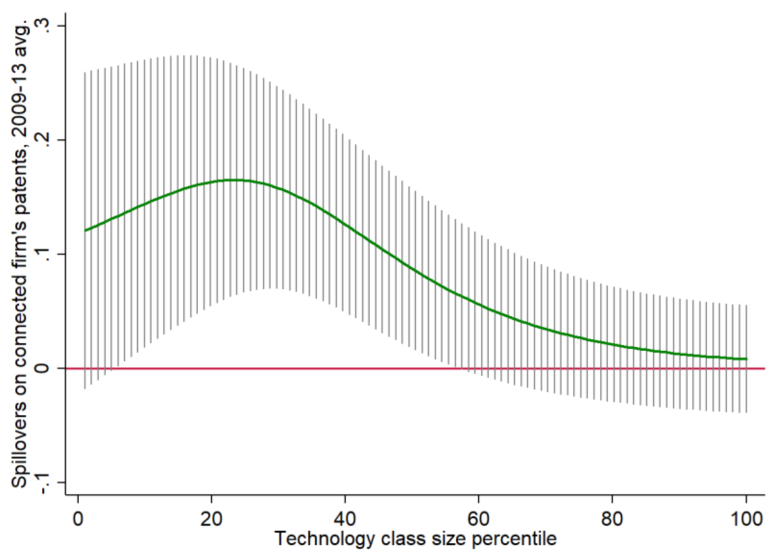
Note: The figure corresponds to column 8 of Table 3, which estimates the discontinuity in firm's average R&D expenditure over 2009-11 at the SME assets threshold of €86m using equation (1). The OLS discontinuity estimate (standard error) at the €86m threshold is 123.2 (52.0), statistically significant at the 5% level. Each point represents a bin of 184 firms on average, over an assets range of €1.5m. (Bin size is large due to data confidentiality requirement, as figure reveals confidential information regarding firms' R&D.)

Figure 3. Discontinuity in average number of patents over 2009-13



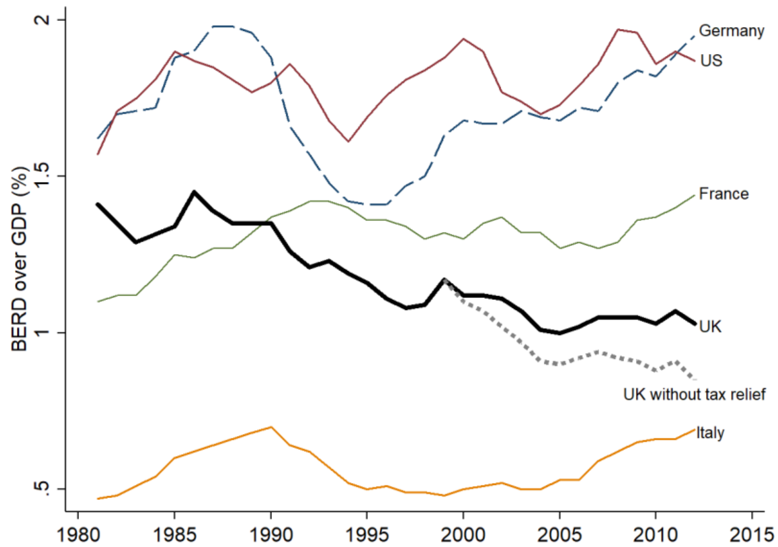
Note: The figure corresponds to column 15 of Table 4, which estimates the discontinuity in firm's average patents over 2009-13 at the SME assets threshold of €86m using equation (2). The OLS discontinuity estimate (standard error) at the threshold is 0.069 (0.026), statistically significant at the 1% level. Each point represents a bin of 184 firms on average, over an assets range of €1.5m. (Bin size is large due to data confidentiality requirement.)

Figure 4. Spillovers on connected firm's patents by primary technology class size



Note: This figure presents semi-parametric estimates of the spillover coefficient on technologically connected firm's patents as a function of the technology class size percentile (the X-axis variable). The semiparametric estimation is based on equation (5), using a Gaussian kernel function of the X-axis variable and a bandwidth of 20% of the range (see Appendix D.4 for details). The grey lines indicate the 90% confidence intervals of the spillover coefficients.

Figure 5. Evolution of Business Enterprise R&D (BERD) over GDP



Note: The data is from OECD MSTI downloaded February 9th, 2016. The dotted line ("UK without tax relief") is the counterfactual R&D intensity in the UK that we estimate in the absence of the R&D Tax Relief Scheme (see subsection 7.3 and Appendix F.3 for details).

Table 1. Baseline sample descriptive statistics

Subsample	Firms with 2007 total assets between €61m and €86m			Firms with 2007 total assets between €86m and €111m			Difference between two subsamples		
Year	2006-08 average	2009-11 average	2009-13 average	2006-08 average	2009-11 average	2009-13 average	2006-08 average	2009-11 average	2009-13 average
Total no. of firms in subsample		3,561			2,327			1,234	
No. of R&D performing firms	160	210		99	119		61	91	
No. of patenting firms	105	104	120	67	57	69	38	47	51
Mean R&D expenditure *(£)*	61,030	80,269		93,788	101,917		-32,758	-21,649	
Mean patent applications (family)	0.061	0.064	0.063	0.067	0.047	0.044	-0.006	0.017	0.018
Mean EPO patent applications	0.078	0.070	0.069	0.074	0.053	0.051	0.004	0.017	0.018
Mean UK patent applications	0.031	0.030	0.030	0.028	0.024	0.024	0.003	0.006	0.006
Mean US patent applications	0.026	0.028	0.028	0.024	0.025	0.025	0.002	0.003	0.003

Note: The baseline sample includes 5,888 firms with total assets in 2007 between €61m and €111m. Total assets are from FAME and are converted to € from £ using HMRC rules. Qualifying R&D expenditure comes from CT600 panel dataset and are converted to 2007 prices. Patent counts come from PATSTAT.

Table 2. Balancing of predetermined covariates

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Dependent variable	**Ln(Sales)**		**Ln(Employment)**		**Ln(Capital)**		**Ln(Value added)**	
Year	2006	2007	2006	2007	2006	2007	2006	2007
Below-assets-threshold indicator (in 2007)	-0.124	0.086	0.117	0.157	0.023	-0.006	-0.076	0.125
	(0.162)	(0.161)	(0.135)	(0.131)	(0.112)	(0.103)	(0.145)	(0.145)
Firms	4,155	4,348	2,973	3,089	4,766	5,078	3,599	3,745

Note: OLS estimates are based on the RD Design analogous to equations (1) and (2). The running variable is total assets in 2007 with a threshold of €86m. Baseline sample includes firms with total assets in 2007 within €25m of the threshold (i.e., between €61m and €111m), for which the corresponding dependent variable is non-missing. Controls include first order polynomials of the running variable separately for each side of the threshold. Robust standard errors are in brackets. Columns 1-2 report pre-treatment covariate tests for sales (from CT600); columns 3-4 – employment (from FAME); columns 5-6 – fixed assets (from FAME); and columns 7-8 – value added, calculated as sales minus imputed materials.

*** denotes statistical significance at 1% level, ** 5% level, * 10% level.

Table 3. Evidence of R&D tax relief effect on R&D (Reduced-form R&D regressions)

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
Dependent variable	**R&D expenditure (£ *'000*)**									
	Before (pre-policy)			After (post-policy)			Before	3yr After	3yr Diff.	LDV
Year	2006	2007	2008	2009	2010	2011	2006-08 average	2009-11 average	3yr After - Before	2009-11 average
Below-assets-threshold indicator (in 2007)	43.4 (50.6)	81.9 (59.2)	63.1 (44.9)	97.3* (51.4)	133. 6** (53.5)	138.9** (55.1)	62.8 (48.9)	123.3** (52.1)	60.4* (31.5)	63.4** (32.1)
Past R&D exp. (£*'000*), 2006-08 average										0.95*** (0.08)
Firms	5,888	5,888	5,888	5,888	5,888	5,888	5,888	5,888	5,888	5,888

Note: OLS estimates are based on the RD Design in equation (1). The running variable is total assets in 2007 with a threshold of €86m. Baseline sample includes firms with total assets in 2007 within €25m of the threshold (i.e., between €61m and €111m). Controls include first order polynomials of the running variable separately for each side of the threshold. Robust standard errors are in brackets. Mean R&D expenditure between 2006 and 2008 was £73,977 and between 2009 and 2011 was £88,824. R&D expenditure is in 2007 real prices.

*** denotes statistical significance at 1% level, ** 5% level, * 10% level.

Table 4: Evidence of R&D tax relief effect on patents (Reduced-form patent regressions)

Panel A.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
Dependent variable	**All patent family count**									
	Before (pre-policy)			After (post-policy)						
Year	2006	2007	2008	2009	2010	2011	2012	2013	2014	2015
Below-assets-threshold indicator (in 2007)	0.002	0.036	0.044	0.095***	0.070**	0.073**	0.050**	0.059*	0.059**	0.047*
	(0.035)	(0.034)	(0.033)	(0.034)	(0.031)	(0.034)	(0.024)	(0.030)	(0.023)	(0.023)
Firms	5,888	5,888	5,888	5,888	5,888	5,888	5,888	5,888	5,888	5,888

Panel B.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
Dependent variable	**All patent family count**									
	Before	3 years After			5 years After			7 years After		
Year	2006-08 average	2009-11 average	3yr After - Before	2009-11 average	2009-13 average	5yr After - Before	2009-13 average	2009-15 average	7yr After - Before	2009-15 average
Below-assets-threshold indicator (in 2007)	0.028	0.079***	0.052**	0.057**	0.069***	0.042*	0.049**	0.065***	0.037*	0.046**
	(0.030)	(0.030)	(0.023)	(0.022)	(0.026)	(0.022)	(0.020)	(0.024)	(0.022)	(0.019)
Past patent family count, 2006-08 average				0.818***			0.729***			0.670***
				(0.107)			(0.106)			(0.106)
Firms	5,888	5,888	5,888	5,888	5,888	5,888	5,888	5,888	5,888	5,888

Note: OLS estimates are based on the RD Design in equation (2). The running variable is total assets in 2007 with a threshold of €86m. Baseline sample includes firms with total assets in 2007 within €25m of the threshold (i.e., between €61m and €111m). Controls include first order polynomials of the running variable separately for each side of the threshold. Robust standard errors are in brackets. Mean all patent family count between 2006 and 2008 was 0.064, between 2009 and 2011 was 0.057, between 2009 and 2013 was 0.055, and between 2009 and 2015 was 0.052.

*** denotes statistical significance at 1% level, ** 5% level, * 10% level.

Table 5: Evidence of R&D tax relief effects on quality-adjusted patents

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)
Dependent variable (2009-13 average)	Baseline	UK patents	EPO patents	US patents	Family size (countries)	Patent citations	Patents in top citation quartile	Chemical/ pharma patents	Non-chem./ pharma patents	ICT patents	Non-ICT patents
Below-assets-threshold indicator (in 2007)	0.069***	0.078**	0.036**	0.041**	0.218**	0.133**	0.033**	0.0149*	0.049**	0.005	0.058**
	(0.026)	(0.031)	(0.016)	(0.016)	(0.108)	(0.067)	(0.013)	(0.008)	(0.021)	(0.003)	(0.024)
Dependent variable mean (2006-08)	*0.064*	*0.076*	*0.030*	*0.026*	*0.254*	*0.292*	*0.031*	*0.009*	*0.050*	*0.003*	*0.059*
Elasticity (estimate divided by mean of dependent variable)	1.08	1.03	1.20	1.58	0.86	0.46	1.06	1.66	0.98	1.67	0.98
Firms	5,888	5,888	5,888	5,888	5,888	5,888	5,888	5,888	5,888	5,888	5,888

Note: OLS estimates are based on the RD Design in equation (2). The running variable is total assets in 2007 with a threshold of €86m. Baseline sample includes firms with total assets in 2007 within €25m of the threshold (i.e., between €61m and €111m). Controls include first order polynomials of the running variable separately for each side of the threshold. Robust standard errors are in brackets. Quality measures are baseline patent family count (column 1), EPO patent count (column 2), UK patent count (column 3), US patent count (column 4), patent by family size count (i.e., patent by country count) (column 5), patent by citation count (column 6), patent count in the top 25% in citation count of their technology class by year cohort (column 7), chemistry/pharmaceutical patent count (column 8), non-chemistry/pharmaceutical patent count (column 9), ICT patent count (column 10), and non-ICT patent count (column 11). Chemistry/pharmaceutical patents include all patents classified into patent sector (3) Chemistry. Information and communication technology (ICT) patents include all patents classified into either patent field (4) Digital communication, (6) Computer technology, or (7) IT methods for management.

*** denotes statistical significance at 1% level, ** 5% level, * 10% level.

Table 6. Returns to R&D on patents (Patent IV regressions)

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Dependent variable (2009-13 average)	**All patent family count**		**UK patent count**		**EPO patent count**		**US patent count**	
Specification	OLS	IV	OLS	IV	OLS	IV	OLS	IV
R&D expenditure *(£ million)*, 2009-11 average	0.206***	0.563**	0.231***	0.629*	0.122***	0.293*	0.121***	0.330**
	(0.070)	(0.282)	(0.084)	(0.328)	(0.046)	(0.153)	(0.043)	(0.166)
Anderson-Rubin test p-value		0.008		0.012		0.025		0.012
Firms	5,888	5,888	5,888	5,888	5,888	5,888	5,888	5,888

Note: IV estimates are based on equation (3). Instrumental variable is the indicator of whether total assets in 2007 is below €86m. Baseline sample includes firms with total assets in 2007 within €25m of the threshold (i.e., between €61m and €111m). Controls include first order polynomials of the running variable (total assets in 2007) separately for each side of the threshold. Robust standard errors are in brackets. Adjusted first-stage F-statistic is 5.6. P-values of Anderson-Rubin weak-instrument-robust inference tests indicate that the IV estimates are statistically different from zero even in the possible case of weak IV.

*** denotes statistical significance at 1% level, ** 5% level, * 10% level.

Table 7. Heterogeneous effects of R&D tax relief by industry's level of financial constraints

	(1)	(2)	(3)	(4)	(5)	(6)
Dependent variable	**R&D expenditure *(£ '000)*, 2009-11 average**			**All patent family count, 2009-13 average**		
Sample	Full	Low Cash/K	High Cash/K	Full	Low Cash/K	High Cash/K
Below-assets-threshold indicator (in 2007)	157.8**	286.6**	-17.8	0.104***	0.171***	-0.003
	(70.6)	(112.0)	(31.4)	(0.040)	(0.064)	(0.011)
Below-assets-threshold indicator # Cash/K	-13.6*			-0.011***		
	(7.7)			(0.004)		
Difference		304.4*** (116.3)			0.174** (0.065)	
Firms	4,504	2,237	2,267	4,504	2,237	2,267

Note: OLS estimates are based on the RD Design in equations (1) and (2). The running variable is total assets in 2007 with a threshold of €86m. Baseline sample includes firms with total assets in 2007 within €25m of the threshold (i.e., between €61m and €111m). Controls include first order polynomials of the running variable separately for each side of the threshold. Robust standard errors are in brackets. Cash/K is calculated as the three-digit SIC industry average of firms' cash and cash equivalents holding as the share of capital over 2000-05. Firms in industries with low Cash/K measure are more likely to be financially constrained. Low (high) Cash/K subsample includes firms with below (above) median industry Cash/K measure. All right-hand-side variables are fully interacted with industry Cash/K measure in columns 1 and 4.

*** denotes statistical significance at 1% level, ** 5% level, * 10% level.

Table 8. R&D technology spillovers on patents

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Specification	Reduced form				First stage		IV	
Dependent variable	**Firm *j*'s all patent family count, 2009-13 average**				**Firm *i*'s R&D exp. *(£ million)*, 2009-11 avg.**		**Firm *j*'s all patent family count, 2009-13 avg.**	
Sample	Full	Full	Large tech. class	Small tech. class	Full	Small tech. class	Full	Small tech. class
Firm *i*'s below-assets-threshold indicator (in 2007)	0.019 (0.012)	0.067*** (0.019)	0.018 (0.011)	0.196** (0.093)	0.933*** (0.013)	0.884*** (0.157)		
Firm *i*'s below-threshold indicator # technology class size ('000)		-0.029*** (0.007)						
Firm *i*'s R&D expenditure *(£ million)*, 2009-11 average							0.020 (0.013)	0.222** (0.110)
Difference			0.178* (0.094)					
Anderson-Rubin test p-value							0.109	0.036
Dependent variable mean (2006-08)	*0.396*	*0.396*	*0.397*	*0.291*	*0.499*	*0.248*	*0.396*	*0.291*
No. of tech. connected firm *j*'s	17,632	17,632	16,477	1,190	17,632	1,190	17,632	1,190
No. of treated firm *i*'s	547	547	487	67	547	67	547	67
No. of three-digit IPC classes	91	91	55	36	91	36	91	36
Observations	203,832	203,832	201,739	2,093	203,832	2,093	203,832	2,093

Note: IV estimates in columns 7 and 8 are based on equation (4). Columns 1-4 report the corresponding reduced-form estimates, which are based on the RD Design in equation (5). Columns 5 and 6 report the corresponding first stage estimates. Each observation is a pair of a treated firm *i* with total assets in 2007 between €61m and €111m and a technologically connected firm *j* (see Section 6 and Appendix D.3). The running variable is firm *i*'s total assets in 2007 with a threshold of €86m. Controls include (i) first order polynomials of the running variable separately for each side of the threshold and (ii) second order polynomial of connected firm *j*'s total assets in 2007. Instrumental variable in columns 7 and 8 is the indicator of whether firm *i*'s total assets in 2007 is below €86m. Standard errors in brackets are clustered by firm *j*. Technology class size is the number of firms whose primary technology class is the said class. Small (large) technology class subsample includes firms whose primary technology classes are below (above) 200 in size (technology class size's 40th percentile). In column 2, all right-hand-side variables are fully interacted with technology class size (in thousands). "Difference" is the test of whether the coefficient of interest is statistically different between columns 3 and 4.

*** denotes statistical significance at 1% level, ** 5% level, * 10% level.

Table 9: Being below the assets threshold as a predictor for SME status

	(1)	(2)	(3)	(4)	(5)	(6)
Dependent variable	**Indicator: Has R&D claims under SME Scheme**					
Year	2009	2010	2011	2008-09	2008-11	2009-11
Below-assets-threshold indicator (in 2007)	0.326***	0.301***	0.184*	0.464***	0.353***	0.248***
	(0.085)	(0.089)	(0.100)	(0.087)	(0.090)	(0.093)
Firms	215	218	248	265	361	333

Note: OLS estimates are based on the RD Design analogous to equations (1) and (2). The running variable is total assets in 2007 with a threshold of €86m. Baseline sample includes firms with total assets in 2007 within €25m of the threshold (i.e., between €61m and €111m). Controls include first order polynomials of the running variable separately for each side of the threshold. Robust standard errors are in brackets. The sample for a certain year (period) effectively includes firms in the baseline sample with R&D tax relief claims in that year (period). A firm's SME status over a period is the maximum of its SME status in each of the year within the period.

*** denotes statistical significance at 1% level, ** 5% level, * 10% level.

APPENDICES: FOR ONLINE PUBLICATION ONLY

Appendix A: Institutional details of the UK R&D Tax Relief Scheme

Appendix B: Data sources and sample construction

Appendix C: Robustness checks and supplementary analyses

Appendix D: R&D technology spillovers

Appendix E: Magnitude of effects and tax-price elasticities

Appendix F: Macro aspects of the R&D Tax Relief Scheme

Appendix Tables:

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Appendix A: Institutional details of the UK R&D Tax Relief Scheme

A.1 Features of the R&D Tax Relief Scheme

The R&D Tax Scheme includes an SME Scheme and a Large Company (LCO) component.[1] Between its introduction in 2000 and 2012, more than 28,500 different companies had made claims under the SME Scheme, and over 7,000 under the Large Company Scheme, claiming more than £9.5bn in total R&D support. The annual amount of R&D support had risen to over £1bn by 2008, reaching £1.4bn in 2012, and covered qualifying R&D expenditure worth £13.2bn (HMRC, 2014).

Enhanced tax deduction. Both SME and Large Company Schemes are volume-based, i.e., the tax relief accrues on the total R&D spending rather than the incremental R&D over a prior base (the main US R&D tax relief scheme is incremental). It works mostly through enhanced deduction of current R&D expenditure from taxable income, thus reducing R&D-performing companies' corporate tax liabilities. The *enhancement rate* is always more generous under the SME Scheme than under the Large Company Scheme.

Example: If a company is allowed an enhancement rate of 75% and spends £10,000 spend on R&D; it can deduct an additional £7,500 (on top of the standard £10,000) for a total of £17,500 from its taxable income before calculating its tax liability.

Payable tax credit. In addition, under the SME Scheme, a company that has taxable loss after the additional deduction can also claim payable tax credit up to the amount of *payable credit rate* × enhanced qualifying R&D expenditure. This payable tax credit can only be used to reduce the company's employers' payroll tax (National Insurance Contributions, NIC) liabilities. Alternatively, the company (either as an SME or as a large company) can choose to carry the loss forward as normal.[2]

Example: If a company is allowed an enhancement rate of 75% and payable credit rate of 14%, spends £10,000 in R&D, and has no taxable income before the additional deduction, it can claim payable tax credit of $0.14 \times £10{,}000 \times (1 + 0.75) = £2{,}450$. If instead the company has £1,500 in taxable income before the additional deduction, it can first use £2,000 of its R&D to reduce its taxable income to zero (i.e., $£1{,}500 = 75\% \times £2{,}000$, then claim payable tax credit of $0.14 \times £8{,}000 \times (1 + 0.75) = £1{,}960$. This latter case is called a combination claim.

To be eligible for R&D tax relief, a company must also spend at least £10,000 a year on qualifying R&D expenditure in an accounting period (see Appendix A.3 for details on what constitutes qualifying R&D expenditure). If an SME works as a subcontractor for a large company, only the subcontractor SME can claim R&D tax relief, under the Large Company Scheme. There is also an upper limit of €7.5m on the total amount of aid a company can receive for any one R&D project under the SME Scheme.[3]

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[1] For further details, see http://www.hmrc.gov.uk/manuals/cirdmanual/CIRD90000.htm (SME Scheme) and http://www.hmrc.gov.uk/manuals/cirdmanual/CIRD85050.htm (Large Company Scheme).

[2] A large company that has taxable loss before the additional deduction therefore may still benefit from R&D tax relief by carrying the enhanced loss forward to further reduce its taxable income in the next period. However, this reduction is only meaningful when the company has enough taxable income in this next period.

[3] Furthermore, an SME already receiving another form of notified state aid for a project cannot claim R&D tax relief for that same project under the SME Scheme (which is also a notified state aid), as total state aid intensity cannot

A.2 SME definition

The UK R&D Tax Relief Scheme's SME (Small and Medium Sized Enterprise) definition is based on total assets ("balance sheet total"), employment ("staff headcount"), and sales ("turnover") as described in Section 2. We summarize the key elements of the definition rules below but for further technical details on these rules see http://www.hmrc.gov.uk/manuals/cirdmanual/CIRD91400.htm.

Ceiling tests and two-year rule. An enterprise passes the SME ceiling tests if (i) its staff headcount and (ii) either its aggregated assets or its aggregated sales fall below the respective ceilings. An enterprise loses (acquires) its SME status if it fails (passes) the ceiling tests over two consecutive accounting periods (two-year rule). The SME ceilings were set according to the European Commission (EC)'s recommendation at the introduction of the R&D Tax Relief Scheme in 2000, which were revised upward (also by the EC) effectively from January 2005. From August 2008, the UK government only for the purpose of the R&D Tax Relief Scheme (see Table A1 and Appendix A.4) doubled the SME ceilings again.

Measurements for ceiling tests. Total assets is the gross amount of assets shown in the company accounts. The staff headcount of an enterprise represents the number of full-time person-years attributable to people who have worked within or for the enterprise during the year under consideration.[4] The staff headcount and financial data used for the ceiling tests are those relating to the latest accounting year, yet financials from previous accounting years also matter due to the two-year rule. Total assets and sales converted to Euros using the exchange rate on the last day of the relevant accounting period, or the average exchange rate throughout that accounting period, whichever is more beneficial for the enterprise.

Account aggregation rules. In the case of an autonomous enterprise, the staff headcount and financial data are determined exclusively based on the consolidated account of the enterprise itself. An autonomous enterprise is one that is not a linked enterprise or a partner enterprise. Generally, an enterprise is autonomous if it has holding of less than 25% of the capital or voting rights in one or more enterprises and/or other enterprises do not have a stake of 25% or more of the capital voting rights in the enterprise.

In the case of a linked enterprise, the ceiling tests are applied to the aggregates of the figures in its own accounts and those from the accounts of all other enterprises to which it is linked (including non-UK ones), unless the account data of the those enterprises are already included through account consolidation. Linked enterprises are those in which one is able to control, directly or indirectly, over the affairs of the other(s).

A.3 Qualifying R&D expenditure

The definition of R&D expenditure that qualifies for the R&D Tax Relief Scheme has been stable over time. Qualifying R&D expenditure must be allowable as a deduction in calculating trading profits, which

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exceed 25% under European Commission's State Aid rules. However, from April 2003 onward, SMEs could claim R&D tax relief for such projects under the Large Company Scheme.

[4] The contributions of part-time workers, or those who work on a seasonal or temporary basis count as appropriate fractions of a full-time person-year. The term staff includes employees, persons seconded to the enterprise, owner-managers, partners (other than sleeping partners); it excludes apprentices or students engaged in vocational training with an apprenticeship or vocational training contract, and any periods or maternity or parental leave.

includes all flow costs, employee costs, materials, utilities, software, or subcontracted R&D expenditure (but only if the contractor is an SME).[5] Formally, the costs must be consistent with the UK accounting definition of R&D under GAAP (accounting standards FRS102 s18, IAS38, FRS105 s13 and SSAP13). In addition, "to quality for R&D, a company must be undertaking a project to seek an advance in science or technology through the resolution of scientific or technological uncertainties. The advance being sought must constitute an advance in the overall knowledge or capability in a field of science or technology, not a company's own state of knowledge or capability alone." More details on what constitutes qualifying R&D expenditure are available at https://www.gov.uk/hmrc-internal-manuals/corporate-intangibles-research-and-development-manual/cird81300 and https://www.gov.uk/hmrc-internal-manuals/corporate-intangibles-research-and-development-manual/cird81900.

A.4 Evolution of the R&D Tax Relief Scheme

2000-02 introduction. Table A1 summarized the evolution of the UK R&D Tax Relief Scheme. It was first introduced in April 2000 only for SMEs (Finance Act 2000, Chapter 17, and Schedule 20), then later extended to large companies starting from April 2002 (Finance Act 2002, Chapter 23, Schedule 12). Between April 2000 and December 2004, the ceilings for staff headcount, assets, and sales were 249, €27m, and €40m respectively. From January 2005, they were raised to 249, €43m, and €50m. This followed European Union guidelines for SME definitions. Throughout the period from April 2000 (April 2002) to March 2008, the enhancement rates were set at 50% for SMEs and 25% for large companies, and the payable credit rate for SMEs was 16%.[6]

2008 changes. As discussed in Section 2, various changes to the scheme became effective at different points in 2008. First, from April 2008, the enhancement rate for large companies was increased from 25% to 30%. Then from August 2008, the enhancement rate for SMEs was increased from 50% to 75% and the payable credit rate for SMEs was reduced from 16% to 14%. That is, the effective state aid intensity in the payable tax credit case increased from 24% (= 1.5×0.16) to 24.5% (= 1.75×0.14).[7]

Also from August 2008, the SME Scheme was extended to "larger" SMEs as the SME ceilings were doubled to 499, €86m, and €100m for staff headcount, total assets, and sales respectively. This change in SME definition is applicable only for the purpose of the R&D tax relief and therefore is the focus of our paper, as it allows us to separate the impacts of the R&D Tax Relief Scheme from those of other programs. It should also be noted that even though these new SME ceilings were announced in Finance Act 2007, the

[5] Qualifying R&D expenditure could include R&D performed outside of the UK by *foreign branches* of UK holding companies, as foreign branches' revenues and costs are directly consolidated into their UK holding companies' tax revenues and costs for UK tax purpose. Qualifying R&D expenditure is unlikely to include R&D performed outside of the UK by *foreign subsidiaries* of UK holding companies, as foreign subsidiaries' net profits are indirectly incorporated into their UK holding companies' tax revenues as dividends for UK tax purpose instead.

[6] One exception to this differential treatment of SMEs and large companies was the Vaccine Research Relief Scheme (VRR) launched in April 2003, which extended the higher 50% additional allowance to cover specific areas of vaccine and drug research conducted in large companies (Finance Act 2003, Chapter 14, Schedule 31). The VRR enhancement rate was later reduced to 40% from August 2008 onward.

[7] The reduction in payable credit rate form 16% down to 14% is to ensure that effective state aid intensity does not exceed the limit of 25% imposed by the European Commission.

date on which they became effective (August 1st, 2008) was announced much later, on July 16th, 2008, less than a month before the effective date.[8]

Later changes. There were tweaks to the system in 2011 and 2012. From April 2011, the SME enhancement rate was increased to 100% and the SME payable credit rate was reduced to 12.5%. From April 2012, the SME enhancement rate was again increased to 125%. However, the SME definition as announced in Finance Act 2007 and the large company enhancement rate of 30% remained unchanged throughout this period.

[8] Finance Act 2007, Section 50 (Appointed Day) Order 2008 of July 16th, 2008.

Appendix B: Data sources and sample construction

B.1 CT600 and RDTC datasets

Overview of the datasets. The CT600 dataset is constructed by the UK tax authority (HMRC) and is a confidential panel dataset of corporate tax returns or assessments made from the returns for the universe of companies that file a corporate tax return in the UK. We can only access the dataset from within an HMRC facility (similar to a US Census Bureau Research Data Center) and merging with other datasets requires approval from HMRC. It is currently not possible to merge CT600 with other government secured datasets available at different facilities.[9] The CT600 dataset covers all accounting periods whose end dates fall between April 1st, 2001 and March 31st, 2012 (we denote the fiscal year ending in March 31st, 2012 by "2011" as most of the data will fall in this calendar year) and consists of all information on the UK Company Tax Return form (which is called the CT600 form). Specifically, an extension of CT600, the Research and Development Tax Credits (RDTC) dataset, provides detailed information on tax relief claims. However, CT600 contains little information on financial statement variables (e.g., assets and employment are not included) as they are not directly required on corporate tax forms.[10]

We convert the original observation unit of firm by accounting period in CT600 to firm by financial year by aggregating all accounting periods the end dates of which fall in the same financial year.[11] This conversion affects a very small number of observations as only 3% of our firm by year observations are aggregates of multiple accounting periods. Our converted dataset then contains 15.7 million firm by year observations over 12 financial years from 2000 to 2011 (covering 3.2 million firms), including 9.1 million firm by year observations over our study period from 2006 to 2011 (covering 2.5 million firms).

Key variables used. Our key variables of interest are those related to firms' R&D tax relief claims from CT600's RDTC dataset, which include the amount of qualifying R&D expenditure each firm has in each year and the scheme under which it makes the claim (SME vs. Large Company Scheme). These variables, originally self-reported by firms on their CT600 forms, have been further validated and corrected by HMRC staff using additional tax processing data available only within the tax authority. It should also be noted that R&D tax relief variables are only available for R&D-tax-relief-claiming firms for the years in which they make the claims. While we believe it is reasonable to assume that non-claiming firms have zero qualifying R&D expenditure, it is not possible to construct their precise SME eligibility without full information on employment, total assets, sales, and ownership structure.

Table B1 shows that over our study period of 2006-11, we observe claims in 53,491 firm by year

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[9] For example, it is currently not possible to merge CT600 with the BERD firm survey which is used to build the national estimate of R&D. Since BERD is a stratified random sample that puts large weight on the biggest R&D performers, we would likely only have a small overlap with firms around the threshold.

[10] The CT600 dataset was further extended to cover up to the end of financial year 2014 in late 2017. However, the corresponding RDTC dataset has not been made available as of the writing of this paper. As a result, we focus on the period between 2009 and 2011, for which we have reliable R&D data, as our post-policy period for R&D analyses. In addition, it is unlikely that our key running variable – total assets in 2007 – has strong predictive power of firm's SME status after 2011. We do use data on sales up to 2013 from this extended CT600 dataset in our firm performance analysis (see Table A14).

[11] Financial year t begins on April 1st of year t and ends on March 31st of year $t+1$.

observations (by 20,730 firms), 81% of which are under the SME Scheme. The total qualifying R&D expenditure and estimated Exchequer costs under the SME Scheme are in nominal terms £11.2bn and £1.8bn respectively; the corresponding figures under the Large Company Scheme are £48.5bn and £3.9bn (excluding claims by SME subcontractors). These figures are in line with the official R&D Tax Relief Scheme statistics released in HMRC (2014).

We also use the data on sales and on investment in plant and machinery from CT600. Sales are annualized to account for different accounting period lengths. CT600 tax-accounting sales, which is calculated using the cash-based method, is not the same as financial-accounting sales (reported in the FAME data – see below), which is calculated using the accrual method and used to determine SME eligibility.[12] However, CT600 sales provides a good measure for firms' growth and performance, given its relatively wide coverage.

B.2 FAME dataset

Overview of the dataset. FAME is a database of UK companies provided by Bureau Van Dijk (BVD), a private sector company. The panel dataset contains companies' balance sheet and income statement data from companies' annual accounts filed at the UK company registry (Companies House), together with additional information on addresses and industry codes. Like other countries, UK regulations for reporting accounting variables vary with company size, so some balance sheet and income statement variables are missing. We discuss the implications of this below.[13] Our FAME dataset also covers 14 financial years from 2000 to 2013 and contains 23.9 million firm by year observations (covering 4.4 million firms), including 11.5 million firm by year observations over our study period of 2006-11 (covering 3.1 million firms).

Key variables used. Our key SME-eligibility variable from FAME (for R&D tax relief purpose) is total assets (i.e., balance sheet total). As almost all UK companies are required by the Companies House to send in their balance sheets for their annual accounts regardless of their size, total assets coverage in FAME is close to complete, at 97% over our study period of 2006-11. On the other hand, sales (financial-accounting sales used to determine SME eligibility) is available for only 15%, as smaller firms are not required to provide their income statements.[14] The proportion of firms that reported employment is even lower, at 5%, as employment reporting is not mandatory. Even in our baseline sample of relatively larger firms (i.e., firms with total assets in 2007 between €61m and €111m); the proportion of firms that reported sales is 67% and employment 55%. For this reason, while we do use FAME sales and employment as

[12] The cash-based method focuses on actual cash receipts rather than their related sales transactions. The accrual methods records sale revenues when they are earned, regardless of whether cash from sales has been collected.

[13] All UK limited companies, public limited companies (PLC), and limited liability partnerships (LLP) are required to file *annual accounts* with the Companies House. An annual account should generally include a balance sheet, an income statement, a director's report, and an audit report. However, smaller companies may be exempt from sending in income statement, director's report, or audit report. All UK registered companies are required to file *annual returns* with the Companies House, which contain information on registered address and industry codes.

[14] Small companies (those having any 2 of the following: (1) sales of £6.5m or less, (2) assets of £3.26m or less, (3) 50 employees or less) are only required to send in balance sheets. Micro-entities (those having any 2 of the following: (1) sales of £632,000 or less, (2) assets of £316,000 or less, (3) 10 employees or less) are only required to send in simplified balance sheets.

running variables in some alternative specifications, our baseline sample and key results are derived using total assets as the running variable.

Besides total assets, sales, and employment, other FAME variables used in our paper include primary industry code, address, capital investment, profits, remuneration, and other financial information.

B.3 PATSTAT dataset

Overview of the dataset. Our patent data are drawn from the World Patent Statistical Database (PATSTAT) maintained by the European Patent Office (EPO).[15] PATSTAT is the largest international patent database available to the research community and includes nearly 70 million patent documents from over 60 patent offices, including all of the major offices such as the United States Patent and Trademark office (USPTO), the Japan patent office (JPO) and the Chinese Patent and Trademark Office (SIPO) in addition to the EPO. Patents filed with the UK Intellectual Property Office are also included. PATSTAT data thus cover close to the population of all worldwide patents between 1900-2015.

PATSTAT reports the name and address of patent applicants, which allows matching individual patents with company databases. The matching between PATSTAT and FAME is implemented by Bureau Van Dijk and is available as part of the ORBIS online platform through a commercial agreement. The quality of the matching is excellent: over our sample period, 94% of patents filed in the UK and 96% of patents filed at the EPO have been matched with their owning company.

Patent family count. A patent in country *c* grants a holder an exclusive right to commercially exploit the invention in that country. Accordingly, she will patent her invention in country *c* if she plans to either market there directly or license to another firm who will sell it there. The set of patents in different countries related to the same invention is called a *patent family*. The vast majority of patent families include only one patent (usually in the home country of the inventor). Importantly, PATSTAT reports not only the unique identifier of each patent application, it also indicates a unique patent family indicator for each patent (we use the DOCDB patent family indicator). This allows us to identify all patent applications filed worldwide by UK-based companies and to avoid double-counting inventions that are protected in several countries.

Our primary measure of innovation is the *number of patent families*, irrespective of where the patents are filed. This proxies for the number of inventions a firm makes. This means that we count the number of patents filed anywhere in the world by firms in our sample, be it at the UK Intellectual Property Office, at the European Patent Office, at the USPTO or anywhere else, but we use information on patent families to make sure that any invention patented in several places is only counted once. Patents are sorted by their first application year (the priority year). We use fractional counts to account for multiple applicants. For example, if two firms jointly apply for a patent, then each firm is attributed one-half of a patent. In practice, only 8% of patents filed by UK-based companies are filed jointly by at least two companies.

Patent quality measures. There are many well-known issues with patents as a measure of innovation. As noted above, not all inventions are patented, although it is reasonable to assume the most valuables ones are, so counting patents screens out many of the low value inventions. Nevertheless, since patents are of

[15] For further details see http://www.epo.org/searching/subscription/raw/product-14-24.html.

very heterogeneous importance we use several approaches to examine how our results change when looking at patent quality.

First, we distinguish between patents filed at the UK patents office and patents files at the EPO and USPTO. [16] Since the financial and administrative cost is about six times higher at the EPO than UK patent office, EPO and USPTO patents will, on average be of higher private value. Relatedly, a second measure of patent quality is the size of patent families, the number of jurisdictions in which each patent is filed. There is evidence that the number of jurisdictions in which a patent is filed is an indicator of its economic value as patenting is costly (see Guellec and Van Pottelsberghe, 2000, and Harhoff et al., 2003).

Third, we use patent citations, also available from PATSTAT. For each patent in the database, we know how many times it was cited by subsequent patents (excluding self-citations). We use the number of subsequent citations (referred to as forward citations) as a measure of value. Again, this measure is well rooted in the patent literature (Hall et al., 2005, Lanjouw and Schankerman, 2004). The disadvantage for our purposes is that we only have a short finite window of time for future citations causing a truncation problem. To address this issue, we benchmark a patent's citations against the distribution of citations to patents in the same patent sector x filing office x filing year cell.

Fourth, another measure of quality is to distinguish by technology class, as some classes (e.g., pharmaceuticals) are likely to be more valuable than others (e.g., business process methods). In addition, patents in PATSTAT patents are categorized based on the International Patent Classification (IPC). We use this to compute the technological scope of a patent. Information on citations and patent technology class additionally allows us to compute more sophisticated measures of patent quality, including (i) the generality index, which measures the patent-class diversity of a patent's forwards citations, and (ii) the originality index, which measures the patent-class diversity of a patent's backward citations.

Finally, we also use patent IPC codes (at three-digit level) to determine a firm's primary technology class, and construct measures of technological proximity and connectedness between firms, which are used to investigate R&D technology spillovers.

B.4 Merging datasets and sample construction

We merge CT600 with FAME using an HMRC-anonymized version of company registration number (CRN), which is a unique regulatory identifier in both datasets. 95% of CT600 firms between 2006 and 2011 also appear in FAME, covering close to 100% of R&D performing firms and 100% percent of patenting firms in this period.[17] Unmatched firms are slightly smaller but not statistically different from matched ones across different variables reported in CT600, including sales, gross trading profits, and gross

[16] Note that because of differences in the "technological scope" of patents across patent offices, two patents filed in the UK may be "merged" into a single patent filed at the EPO. In this case, these three patents will constitute a single patent family and the number of patent families is smaller than the number of UK patents. This configuration happens very rarely, however.

[17] Out of 2,495,944 firms present in CT600 between 2006 and 2011, 2,358,948 firms are matched to FAME (94.5% match rate). Over the same period, 20,627 out of 20,730 R&D-performing firms and 9,376 out of 9,420 patenting firms are matched to FAME (99.5% match rate).

and net corporate tax chargeable.[18] Furthermore, that the match rate is less than 100% is due to CRN entering error in FAME, which happens more often among firms that are much smaller than those around SME-eligibility thresholds.[19] For these reasons, we believe sample selection due to incomplete matching between CT600 and FAME is unlikely to be an issue for us.[20]

PATSTAT has been merged with FAME by BVD. As PATSAT comprehensively covers all UK patenting firms, we can safely infer that non-matched firms have zero patents. Over our study period of 2006-11, 9,420 out of 2.5 million CT600 firms claim a total of 46,405 patent families (in 17,293 firm by year observations), including 23,617 higher-quality EPO patents. These patents cover 90% of the total recorded in PATSTAT.

From the merged master dataset, we construct our baseline sample based on total assets in 2007, as it is our key running variable. Specifically, our baseline sample includes 5,888 firms that satisfy the two following conditions: (1) the firm's total assets in 2007 is between €61m and €111m (within €25m below and above the SME threshold of €86m), and (2) the firm appears in CT600 in 2008 (to exclude firms exiting before the policy change in 2008). Baseline sample descriptive statistics are summarized in Table 1 and discussed in detail in subsection 4.2.

B.5 Further notes on variable construction

Converting sterling to euros. As FAME total assets and sales are reported in sterling while the corresponding SME ceilings are set in euros, we convert sterling to euros using the exact same rule used by HMRC for tax purposes. That is, the conversion should be done using the exchange rate on the last day of the relevant accounting period or the average daily exchange rate throughout that accounting period, whichever is more beneficial for the enterprise. The daily exchange rate is obtained from the OECD, using the exact the same method as used by HMRC.

Qualifying R&D expenditure. For qualifying R&D expenditure, we do not include the amounts claimed by SME subcontractors, which do not benefit from more generous reliefs under the SME Scheme. Since SME subcontracting makes up only a small portion of the overall R&D Tax Relief Scheme, we confirm excluding SME subcontracting does not materially affect our key findings. To account for price differences across years, we also convert nominal values of R&D expenditure to their real values in 2007 price, using UK annual CPI as reported in the World Bank Economic Indicators database.[21]

Winsorizing key variables. We address the presence of outliers in R&D spending or patenting by

[18] Differences (standard errors) between matched and unmatched firms in sales (£'000), gross trading profits (£), gross corporate tax chargeable (£) and net corporate tax chargeable (£) are 970 (3,286), 8,969 (13,703), 3,497 (3,898) and 1,961 (2,291) respectively. None of these differences are statistically significant at conventional level.

[19] Because of confidentiality concerns, we do not get to work directly with CRNs but an anonymized version of CRNs provided by the HMRC Datalab for both FAME and CT600 datasets. This prevents us from further cleaning and matching of initially unmatched firms due to above issue.

[20] The correlation between ln(sales) from CT600 and ln(sales) from FAME is 0.90. As noted above, the variables are not measured in the same way, but the fact that their correlation is high is reassuring that the match is well performed.

[21] Ratios of current-£ to 2007-£ derived using UK annual CPI are 1.023 for 2006, 1.000 for 2007, 0.965 for 2008, 0.945 for 2009, 0.915 for 2010, and 0.875 for 2011.

winsorizing our key outcome variables, which include qualifying R&D expenditure and number of all patents as well as number of EPO patents, UK patents, and US patents. Specifically, for each variable, the top 2.5% of non-zero values in each year within the sample of firms with 2007 total assets between €46m and €126m are set to the corresponding 97.5 percentile value (i.e., winsorization at 2.5% of non-zero values). This translates into "winsorizing" the R&D of top 5 to 6 R&D spenders and the number of patents of top 2 to 4 patentees in the baseline sample in each year. It should be noted that our key findings are robust to alternative choices of winsorization window (e.g., 1% or 5% instead of 2.5%), or to excluding outliers instead of winsorizing outcome variables (see Tables A4, A5, and A6).

Financial constraint measures. We construct an industry-level measure of financial constraints as the average cash holdings to capital ratio in each three-digit SIC industry. This ratio is computed using FAME data for the universe of UK firms over 2000-05. Cash holding is the amount of cash and cash equivalents on the balance sheet; capital is proxied by fixed assets. We first (i) average cash holding and capital within firm over 2000-05, then (ii) calculate the cash holding to capital ratio at the firm level, and finally (iii) average this ratio across firms by industry. Constructing the measure at the two-digit and four-digit SIC industry levels, or using cash flow instead of cash holding, yields qualitatively similar results.

Total factor productivity (TFP). TFP is calculated as $\ln(value\ added) - \propto_k \ln(capital) - \propto_l \ln(wages)$, in which (i) value added is sales minus imputed materials, (ii) capital is proxied by fixed assets, (iii) wages is as reported in FAME, and (iv) $\propto_k$ and $\propto_l$ are estimated separately for each two-digit SIC industry across all UK firms in FAME over the 2000-05 period, using Olley-Pakes (1996) production function estimation.

Construction of other variables is generally detailed in the notes to tables.

Appendix C: Robustness checks and supplementary analyses

C.1 Bunching at the SME thresholds in 2007 and later years

Assets, sales, and employment distributions in 2007. Figure 1 shows that firms' 2007 assets distribution was continuous around the 2008 new SME threshold of €86m. The corresponding McCrary test, which estimates the discontinuity in firms' 2007 assets distribution at the said threshold, yields a discontinuity estimate (log difference in density height at the threshold) (standard error) of -0.026 (0.088), which is not statistically different from zero. Using available data on sales and employment, similar McCrary tests also suggest that in 2007, there was no bunching below the new SME sales threshold of €100m or employment threshold of 499. Furthermore, there was no bunching below the assets threshold among firms for whom the assets threshold was binding (firms that met the employment criterion but did not meet the sales one). The evidence further confirms that firms had not immediately manipulated their financials in response to the news of the policy change as laid out in the Finance Act 2007, especially when the new policy's effective date was only announced a year later, in July 2008.

Assets distributions in pre- and post-policy periods. As discussed in Sections 2 and 3, we focus on the 2007 value of total assets as our primary running variable to avoid potential endogenous sorting of firms across the threshold once the policy effective date was announced in mid-2008. We test the validity of our choice by estimating firms' assets distribution at the SME threshold of €86m in each year from 2006 to 2011 using the McCrary test. For 2006 and 2007, the tests confirm that firms did not manipulate their total assets to benefit from the SME Scheme before 2008. The log differences in density height at €86m are not statistically different from zero, with coefficients (standard errors) of 0.029 (0.065) in 2006, -0.026 (0.088) in 2007. On the other hand, there is some graphical evidence of firms' bunching right below €86m from 2009 onward, consistent with rational responses to the policy, although they are small and insignificant. [22]

Figure A1, which pools together the two years before the policy change (2006-07), shows a discontinuity estimate (standard error) of 0.013 (0.056), while Figure A2, which pools together the three years after the change, shows a discontinuity estimate (standard error) of -0.072 (0.045). Endogenous sorting did seem to happen, but only after the policy became effective. If knowledge production benefits from economy of scale, then firm's attempt to "stay small" to benefit from the SME scheme could lead to an underestimation of the true returns to R&D on patents using equation (3) (and vice versa). However, the small difference in firm size between those right below and above the threshold is unlikely to generate bias large enough to be of first order concern.

C.2 Conditioning on not exceeding the SME employment threshold

We expect that equations (1) and (2)'s estimates of the effects of being the below the SME threshold (i.e., the reduced-form effects of the SME Scheme) on R&D and patents exist only among firms for which

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[22] We exclude 2008 as the increase in deduction rate for large companies became effective before the effective date for the changes in the SME Scheme (including increase in deduction rate for SMEs and SME definition change) was announced much later in the year. As such, it is hard to predict which way the bunching would happen in this year, or if it would happen at all.

the assets criterion is binding. We examine this hypothesis in Table A3 by splitting the baseline sample into subsamples of firms whose 2007 employment did not exceed the SME employment threshold of 499 (Panel A), and those whose 2007 employment did (Panel B). Note that the SME ceiling tests require that firms must first meet the employment criterion before either assets or sales criterion could be considered. However, information on employment is available for 3,100 out of 5,888 firms in our baseline sample.

Panel A reports large and statistically significant jumps in both R&D and patents at the assets threshold from 2009 onward among firms for which the assets criterion was binding. Furthermore, these discontinuities are considerably larger than those reported in Tables 3 and 4, which are estimated using the full baseline sample, especially after accounting for firm's pre-policy R&D and patents (columns 3, 6, 8 and 10). On the other hand, in Panel B, we find no similar effect on either R&D or patents among larger-employment-sized firms for which the assets criterion was not binding, which serves as a placebo test.

These results also suggest that Panel B's firms should be excluded from the baseline sample if employment were observed for all firms. However, as employment is selectively missing for close to half of the baseline sample, we decide not to do so in our main analyses to avoid potential selection issues.

C.3 Placebo threshold tests

To examine if the jumps in R&D and patents are unique to the SME assets threshold of €86m, we run a series of placebo tests at all possible integer thresholds between €71m and €101m using the same RD specification in equations (1) and (2) and the same €25m sample bandwidth. Figures A5 and A6 show that the estimated discontinuities in post-policy R&D (average over 2009-11) and patents (average over 2009-13) peak at €86m and are statistically significant only near this true SME threshold (due to effect contamination from the true threshold).

In fact, if we adjust the placebo-threshold estimation samples to not overlap with the true threshold, then *all* resulting coefficients are small and not statistically different from zero. For example, using a placebo threshold of €71m with as an upper bound the true threshold of €86m and as a lower bound €46m (€25m below the placebo threshold) yields a discontinuity estimate (standard error) of -8.0 (38.0) for R&D outcome, and using a placebo threshold of €101m with as a lower bound the true threshold of €86m and as an upper bound €116m (€25m above the placebo threshold) yields -53.1 (85.1). These coefficients are small in magnitude compare to that estimated at the true threshold of 123.3 (52.1). These results further confirm that the discontinuities in R&D and patents exist only the true SME threshold, as results of the more generous SME Scheme after the 2008 policy change.

C.4 Robustness tests and other estimation models

Our R&D (equation 1, Table 3), patent (equation 2, Table 4), and IV (equation 3, Table 6) results are robust to a wide range of robustness tests, as reported in Tables A4, A5, and A6 respectively. As these tables have the same structure, the column reference below applies to all three tables.

Higher order polynomial controls. First, if we add second (column 1) or third (column 2) order polynomials to the baseline specifications, we obtain discontinuity estimates comparable in magnitude to the baseline results, although they are not always statistically significant. Importantly, in all specifications, the coefficient on the higher order assets terms are not statistically significant, and we cannot reject that the higher order terms are jointly zero. This supports our choice to use first order polynomial controls as per Gelman and Imbens's (2018) advice.

Alternative bandwidths and weights. Second, columns 3 and 4 employ Epanechnikov and triangular kernel weights, columns 5 and 6 narrower sample bandwidths of €15m or €20m, and columns 7 to 10 larger sample bandwidths of €30m or €35m respectively. In columns 7 and 8, we add a second order polynomial to improve the fit given the larger bandwidths (the coefficients on the second order assets terms are significant for both bandwidths). Alternatively, in columns 9 and 10, we use triangular kernel weights to give more weights to firms closer to the threshold. Almost all specifications yield statistically significant discontinuity estimates of comparable magnitude to our baseline results, confirming that the latter are not driven by our sample bandwidth choice.

Additional control variables. Third, the discontinuity estimates are quantitatively similar to our baseline results when we add industry (column 11), location (column 12), or industry-by-location (column 13) fixed effects, as expected in an RD Design. We also consider controlling for lagged dependent variable in 2007 (column 17 of Tables A4 and A5) instead of its average over 2006-08, which generates almost identical estimates to those in column 10 of Table 3 and column 17 of Table 4. In Table A6, controlling for either construction of lagged dependent variable only slightly reduces the IV estimate of the returns to R&D (columns 17 and 18).

Alternative data trimming rules. Fourth, we examine winsorizing R&D and patent data at 1% (column 14) or 5% (column 15) instead of 2.5% as for the baseline sample. We also explore dropping outliers in either R&D or patents (or both) as an alternative way to address outliers (column 16). These expectedly affect the magnitude of discontinuity estimates, but not the qualitatively finding of the presence of statistically significant discontinuities in R&D and patents at the SME assets threshold.

Other estimation models. Fifth, in columns 18, we implement the Calonico, Catteneo, and Titunik's (CCT) (2014) robust bias-corrected optimal bandwidth RD Design (using the default triangular kernel weights), which again yields quantitatively similar results to our baseline. The CCT selected optimal bandwidth for R&D outcome is €20.3m and for patent outcome is €31.2m, which guides our baseline sample bandwidth choice of €25m. Finally, we obtain statistically significant estimates of comparable magnitude when using count data models, i.e., Poisson (column 19) and Negative Binomial (column 20), instead of OLS, to allow for a proportional effect on R&D (as in a semi-log specification).

C.5 Policy effects on non-qualifying expense categories

We estimate equation (1) with various non-R&D expense categories as the outcome variables. Table A14 reports statistically insignificant discontinuities across these expenses, among both all baseline firms (columns 1-5) and only R&D-performing firms (columns 6-10). These categories include: (i) total administrative expenses (columns 1 and 5), (ii) total administrative expenses minuses qualifying R&D expenditure (columns 2 and 6), (iii) total expenses minuses qualifying R&D expenditure (columns 3 and 8), (iv) imputed capital expenditure (columns 4 and 9), and (v) qualifying machinery and plant investments for capital allowance tax relief purpose (columns 5 and 10). The magnitude of the coefficients (either positive or negative) are immaterial compared to firms' average R&D or spending in the corresponding expense categories. This suggests that firms benefitting from the SME Scheme did not also increase complementary non-R&D investments when they increased R&D spending in response to the policy. The results also imply that relabeling is unlikely a first order concern in our context, as it should lead to decreases in non-qualifying expense categories (as found in Chen et al., 2019, in the context of China), which we do not observe. Furthermore, relabeling, had it happened, could not explain the effect the policy had on patents, and would only bias equation (6)'s IV estimate downward.

C.6 Exploiting other elements of the SME definition

Using sales or employment criterion. In Table A16, we estimate analogous RD regressions (equations 1 and 2) using other elements of the SME definition, namely sales and employment (also in 2007), to estimate the reduced-form effects of the SME Scheme. While we still find positive effects on R&D and patents using either the sales or the employment criterion, these effects are not always statistically significant (Panel A). They are also of smaller magnitude compared to our baseline effects (estimated using the assets criterion) when taking into consideration the baseline pre-policy R&D and patent means of the respective sample. The proportional effects (the RD coefficient divided by the pre-policy mean of the dependent variable) for R&D using assets, sales, and employment criteria are 1.67, 1.16, and 0.41 respectively (columns 1, 3, and 7), and for patents are 1.09, 0.31, and 0.41 (columns 2, 4, and 8). When we restrict the sample to firms for which the sales criterion binds (firms that were above than assets threshold), the proportional effects resulting from using sales as the running variable increase (although they are still lower than our baseline results), as meeting the sales criterion is a better predictor of SME status in this subsample (columns 5 and 6).

We must interpret these results with caution because, because as emphasized in subsection 4.1, there are many missing values on sales and especially employment, and these are unlikely to be random. Furthermore, using available data on sales, we also find evidence that the assets criterion is more binding than the sales one, suggesting that being below the SME sales threshold is a pretty weak instrument for firm's eligibility for the SME Scheme (see below for further details).

Indeed, in Panel B, we further examine whether combining the different SME criteria could increase the efficiency of our estimates but find no significant improvement. The baseline below-assets-threshold indicator usually generates large and statistically significant effects on both R&D and patents, while the below-sales-threshold indicator does not. This is consistent with the observation that the assets criterion is more binding and therefore the below-assets-threshold indicator is a more precise instrument for firm's SME status. Joint F-statistics for below-assets-threshold and below-sales-threshold indicators indicate that their effects on R&D and patents are always jointly significant. Finally, the IV estimates of the returns to R&D on patents using both criteria as instrumental variables for R&D are similar to our baseline estimates (columns 3 and 6). However, they are less precise due to the inclusion of an additional weak below-sales-threshold indicator instrument.

SME criterion binding ratio. We find evidence that the assets criterion is more binding than the sales one. A firm is considered an SME if it meets either one of the criteria, thus the assets criterion is binding only when the firm already fails the sales one and vice versa. We define the binding/non-binding ratio for a criterion as the number of firms for which the criterion binds divided by the number of firms for which the criterion does not bind.

Specifically, we calculate the binding/non-binding ratio for the *assets* criterion as the number of firms with 2007 sales in [€100m, €180m] (firms for which the assets criterion binds), divided by the number of firms with 2007 sales in [€20m, €100m] (firms which also meet the sales criterion), conditioned on firms' 2007 total assets being in [€36m, €136m] (+/-€50m window around the assets threshold of €86m).

Similarly, the same ratio for the *sales* criterion is the number of firms with 2007 assets in [€86m, €166m] (firms for which the sales criterion binds), divided by the number of firms with 2007 assets in [€6m, €86m] (firms which already meet the assets criterion), conditioned on firms' 2007 sales being in [€50m, €150m] (+/-€50m window around the sales threshold of €100m).

The binding/non-binding ratio for the assets criterion is 0.36, considerably higher than that for the sales criterion of 0.20, as visually presented in Figure A11. This implies that the below-assets-threshold indicator is a more precise instrument for firm's SME status than the below-sales-threshold indicator, consistent with the results reported in Table A16 and discussed above. Finally, the qualitative results that the assets criterion is more binding than the sales criterion does not change when we pick different windows to calculate the binding/non-binding ratios.

Appendix D: R&D technology spillovers

D.1 Framework for estimating R&D technology spillovers

We start with a general system of spillover equations in which each firm *j*'s innovation output (patents) depends on (i) its own R&D, (ii) all connected firms' R&D, and (iii) all connected firms' innovation outputs, as specified by:

$$PAT_j = \kappa R_j + \psi \frac{\sum_{i\neq j}^{N} R_i}{N-1} + \pi \frac{\sum_{i\neq j}^{N} PAT_i}{N-1} + \nu_j \tag{D1}$$

Where N is the number of firms in firm *j*'s technology class, and $\frac{\sum_{i\neq j}^{N} R_i}{N-1}$ and $\frac{\sum_{i\neq j}^{N} PAT_i}{N-1}$ denote average R&D and patents among $N-1$ firms in the same technology class to whom firm *j* is connected. Parameter κ reflects the direct own R&D effect of R_j; $\frac{\psi}{N-1}$ is the direct spillover effect of other firms' R&D, and $\frac{\pi}{N-1}$ is the direct spillover effect of other firms' patents. Within this system, an increase in own R&D R_j impacts PAT_j via both (i) a direct effect from R_j to PAT_j and (ii) an *indirect* effect from R_j to PAT_i to PAT_j. Similarly, an increase in R_i impacts PAT_j via both (i) direct spillover from R_i to PAT_j and (ii) indirect spillover from R_i to PAT_i to PAT_j.

Solving equation system (D1) by substitution gives the following equation:

$$PAT_j = \gamma R_j + \xi R_i + \xi \sum_{k\neq j,i}^{N} R_k + \eta_j \tag{D2),}$$

where

$$\gamma = \frac{\kappa + \pi\psi + (N-2)(1-\pi)\kappa}{(1-\pi)(N-1+\pi)},$$

and

$$\xi = \frac{\psi + \pi\kappa}{(1-\pi)(N-1+\pi)}.$$

Here, γ captures the *net* own R&D effect of R_j on PAT_j, where $\frac{\kappa+(N-2)(1-\pi)\kappa}{(1-\pi)(N-1+\pi)}$ and $\frac{\pi\psi}{(1-\pi)(N-1+\pi)}$ are the direct and indirect own effects respectively. Similarly, ξ captures the *net* R&D spillover effect of R_i on PAT_j, where $\frac{\psi}{(1-\pi)(N-1+\pi)}$ and $\frac{\pi\kappa}{(1-\pi)(N-1+\pi)}$ are respectively the direct and indirect spillover effects.

Estimating γ. Equation (D2) can be rewritten as equation (3) in the main text by absorbing $\xi R_i + \xi \sum_{k\neq j,i}^{N} R_k + \eta_j$ (after partialling out the running-variable polynomial controls) into equation (3)'s error term. As $E_{j,2007}$ is as good as random in the RD Design, it is also conditionally uncorrelated with R_i and R_k under mild sufficient conditions (discussed in subsection D.2 below). Then it remains the case that $E_{j,2007}$ satisfies the exclusion restriction that $E_{j,2007}$ affects PAT_j only via R_j and equation (3)'s IV specification thereby consistently estimates γ, the net own R&D effect of R_j on PAT_j.

Estimatingξ. Equation (D2) can also be rewritten as equation (4) by absorbing $\kappa R_j + \xi \sum_{k\neq j,i}^{N} R_k + \eta_j$

(after partialling out the running-variable controls) into equation (4)'s error term. Similarly, as $E_{i,2007}$ is as good as random in the RD Design, it is also conditionally uncorrelated with R_j and R_k. Then $E_{i,2007}$ satisfies the exclusion restriction that $E_{i,2007}$ affects PAT_j only via R_i and equation (4)'s IV specification thereby consistent estimates ξ, the net R&D spillover effect of R_i on PAT_j.

ξ as a function of *N*. Equation (D1) specifies R&D and patent spillovers as a function of *average* R&D and patents of all connected firms. For fixed values of ψ and π, the *net* spillover effect of a single firm *i*'s R&D on firm *j*'s patents $\xi = \frac{\psi+\pi\kappa}{(1-\pi)(N-1+\pi)}$ quickly decreases with their technology class size N. This reflects the observation that in large technology classes, a single firm has relatively small impact on the field's average technology (as measured by average R&D and patents in equation D1) and thereby other firms' innovations. Indeed, the data show evidence consistent with this hypothesis (as discussed in Section 6 in the main text). Furthermore, Figure 5, which plots $\hat{\theta}$ as a function of N, closely tracks how ξ is expected to evolve with N based on the above formula (note that empirically, the first-stage coefficient θ/ξ does not vary with N).

Direct versus indirect effects. It is not possible to separately identify three parameters κ, ψ, and π from only two estimates $\hat{\gamma}$ and $\hat{\xi}$. However, κ and ψ *are* identified for a given value of π (provided that N is also known). Conceptually, π captures the spillovers from patents that are beyond the spillovers from R&D knowledge creation. It is therefore reasonable to think that π is small if not zero, as it is difficult to think of a channel for such spillover. (One possible passage could be that patents allow for knowledge disclosure, which then facilitates technology spillovers.) When $\pi = 0$, $\gamma = \kappa$ and $\xi = \psi$. That is, both own R&D and R&D spillover indirect effects are zero, thus the net effects equal the direct effects. On the other hand, at the other extreme, when $\pi = 1$ (which is highly unlikely),[23] ψ is negative under the reasonable assumption that $\gamma > \xi$. Furthermore, for given values of γ and ξ, both κ and ψ are decreasing in π. (That is, for given values of the net effects, the direct effects are smaller when π, and thus the indirect effects, is larger.)

Using our empirical estimates of $\hat{\gamma}$ = 0.563 (column (2) of Table 6) and $\hat{\xi}$ = 0.222 (column (8) of Table 8), we find that the $\bar{\pi}$ threshold at which ψ becomes negative increases extremely quickly with N and reaches 0.9 at N < 20 (Figure A7). That is, ψ is positive for most combinations of π and N. Relatedly, Figure A8 plots κ and $\frac{\psi}{N-1}$ as a function of π at the "average" value of N among the small-technology class sample used to estimate ξ (the sample in Table 8, column (8)).[24] It is shown that $\frac{\psi}{N-1}$ is positive for any

[23] Note that it is not possible for π to be greater than 1, as the system will then explode.

[24] To derive the "average" value of N among a sample of heterogenous technology class size, we employ the following bounding approace. First, we rewrite equation (D2) with γ and ξ themselves being functions of N:

$$PAT_j = \gamma(N_j)R_j + \xi(N_j)R_i + \xi(N_j)\sum_{k\neq j,i}^{N} R_k + \eta_j.$$

Under the assumption that R_i and R_j are orthogonal to $N_i = N_j$, it can be shown that:

$$\hat{\xi} = \mathbb{E}(\xi(N)) = \frac{\psi+\pi\kappa}{1-\pi}\mathbb{E}\left(\frac{1}{N-1+\pi}\right).$$

reasonable value of π (i.e., π smaller than 0.98), implying that while we cannot precisely identify the direct R&D spillover effect ψ, it is highly likely to be positive given our $\hat{\gamma}$ and $\hat{\xi}$ estimates.

D.2 Orthogonality between $\mathbf{E_{i,2007}}$ and firm *j*'s characteristics

We argue that for any characteristic U_j of firm $j(i)$ connected to firm i, the distribution of $U_{j(i)}$ is smooth as firm i's size crosses the threshold of €86m, therefore $\lim_{z_i \to 86-} \mathbb{E}\left[U_{j(i)} | E_i = 1\right] = \lim_{z_i \to 86+} \mathbb{E}\left[U_{j(i)} | E_i = 0\right]$, and θ could be correctly identified in equation 4. In this case, the standard "local randomization" result from Lee and Lemieux (2010, pp. 295-6) is extended to connected firms under three (sufficient) conditions: (i) there are some (possibly very small) perturbations so that firms do not have full control of their running variable (assets size) (Lee and Lemieux's (2010) standard RD Design condition), (ii) the size distribution of connected firms $\{j(i)\}$ is smooth for each firm i, and (iii) for each firm i, this size distribution changes smoothly with firm i's size. Conditions (ii) and (iii) warranty that the set of connected firms $\{j(i)\}$ does not change abruptly when firm i's size crosses the threshold. This condition holds naturally given our definition of connected firms. It could fail under certain extreme cases, e.g., when $\{j(i)\}$ comprise all firms with exactly the same size as i, in which case all connected firms $j(i)$ abruptly switch side when firm i crosses the threshold.

Given the above, controlling for $g(z_{j,2007})$ (or $E_{j,2007}$) as in equations (4) and (5) is not needed for identification, although it helps improve precision as connected firm j's are drawn from a wide support in terms of firm size (as captured by $z_{j,2007}$). All of our results are robust to dropping this inessential $g(z_{j,2007})$ polynomial control, or adding $E_{j,2007}$ as an additional control variable (as discussed below in D.5).

D.3 Technological connectedness definition

We consider two firms to be technologically connected if (i) most of their patents are in the same three-digit IPC technology class and (ii) the Jaffe (1986) technological proximity between them is above median (0.75). Both criteria are determined based on firms' pre-policy patent portfolios over 2000-08, thus technological connectedness is defined only among firms which patented during this period. For criterion (i), we define a firm's primary technology class as the three-digit IPC technology class single in which the firm filed the most patent applications. Two firms satisfy criterion (i) if they have the same primary technology class. The size of a technology class is the number of firms whose primary technology class is the said technology class. Over 2000-08, UK firms patented primarily in 113 technology classes (out of 123 three-digit IPC technology classes), whose sizes range from 11 to 2734.

For criterion (ii), we follow Jaffe (1986) in defining proximity as the uncentered angular correlation

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Notice that $\mathbb{E}\left(\frac{1}{N}\right) < \mathbb{E}\left(\frac{1}{N-1+\pi}\right) < \mathbb{E}\left(\frac{1}{N-1}\right)$, which allows us to construct an empirical lower and upper bounds for $\mathbb{E}\left(\frac{1}{N-1+\pi}\right)$ when π is not known. The bounds constructed for small-technology class sample imply that the "average" N should fall between 108.7 and 109.3 for $\mathbb{E}\left(\frac{1}{N-1+\pi}\right)$ to fall between these bounds. We thus use 109 as the "average" value for N.

between the vectors of the proportion of patents taken out in each technology class $\omega_{ij} = \frac{F_i F_j'}{(F_i F_i')^{\frac{1}{2}}(F_j F_j')^{\frac{1}{2}}}$, where $F_i = (F_{i1}, \dots, F_{i\Upsilon})$ is a $1 \times \Upsilon$ vector where $F_{i\tau} = \frac{n_{i\tau}}{n_i}$ is firm i's number of patents in technology field τ as a share of firm i's total number of patents. The Jaffe technological proximity equals 1 if firms i and j have identical patent technology class distribution and 0 if the firms patent in entirely different technology classes. It has been shown that this Jaffe measure delivers similar results to more sophisticated measures of proximity (Bloom, Schankerman, and Van Reenen, 2013). The 25th-75th percentile range of Jaffe technological proximity among firms having the same primary technology class is 0.63-0.94, with a median/mean of 0.75. We thus pick 0.75 as the cut-off for criterion (ii), yet our qualitative results are not sensitive to this cut-off choice (see Appendix D.5 for more details).

D.4 Semi-parametric estimation of spillovers by technology class size

We modify the spillover regression in equation (5) from Section 6 to model the potentially heterogeneous effect of baseline firm i's likeliness of eligibility for the SME scheme on connected firm j's average patents over 2009-13 as a non-parametric function of the primary technology class size (measured in percentile and denoted as x), as in the following equation (D3):

$$PAT_j = \alpha_5(x) + \theta(x)E_{i,2007} + f_5(z_{i,2007}, x) + g_5(z_{j,2007}, x) + \varepsilon_{5ij}$$

Figure 5 plots the estimated function $\theta(x)$ of the spillover effect based on primary technology class size percentile. It is estimated from semi-parametric local linear regressions of equation (4) at each value of x, weighted by a Gaussian kernel with a bandwidth of 20% (with x ranging from 1 to 100). The observed pattern is similar across a wide range of bandwidths.

D.5 Robustness of R&D spillover estimates

Clustering scheme. First, all of our key results remain statistically significant, although the coefficients are expectedly less precisely estimate, under (i) alternative clustering scheme by firm *i*, or (ii) more conservative clustering scheme by the dyad's primary technology class.

Polynomial controls. Second, these results are robust to employing different polynomial controls for $z_{i,2007}$, $z_{j,2007}$, $E_{j,2007}$, and pre-policy patents. These include:

i. Dropping $g(z_{j,2007})$ polynomial control, as it is not needed for in the RD Design,
ii. Employing first-order polynomial of $z_{j,2007}$ or $\log(z_{j,2007})$ for $g(z_{j,2007})$ in place of second-order polynomial,
iii. Adding $E_{j,2007}$ as an additional control variable, together with either a first- or second-order polynomial of $z_{j,2007}$ separately on each side of the SME assets threshold, and
iv. Controlling for firm *j*'s pre-policy patents $PAT_{j,06-08}$ (see Figure A10).

Separately, we find that the policy spillover estimate (θ) is larger among firm *j*'s that were above the eligibility threshold, suggesting that spillovers and direct policy effect are substitutes.

Technological connectedness. Third, we consider alternative definitions of technological connectedness. Extending the definition of technological connectedness to all firm dyads patenting primarily in the same three-digit IPC technology class expectedly results in smaller spillover estimates. More importantly, we observe the same pattern that spillovers are large and statistically significant only in small technology classes (Figure A9). Similarly, extending the definition of technological connectedness to all dyads whose Jaffe (1986) technological proximity is above 0.75 yields statistically significant spillover estimates of comparable magnitude among firm dyads in small technology classes (as determined by the size of firm *i*'s primary technology class). Finally, we obtain the same qualitative results from varying the Jaffe (1986) technological proximity cut-off.

Post-policy period. Fourth, we examine the evolution of spillovers over alternative post-policy periods. Using patent data through 2015 or only 2011 (instead of 2013) both give statistically significant spillover estimates of comparable magnitude among firm dyad in small technology classes. On the other hand, the corresponding estimates for the pre-policy years (2006-08) are not statistically significant. These results are visually summarized in Figure A10, which plots $\widehat{\theta}$ over time using equation (5) with an additional control for firm j's pre-policy patents $PAT_{j,06-08}$.[25]

Spillovers on R&D. On the other hand, we do not find similarly robust spillover estimates on firm *j*'s R&D, especially after controlling for firm j's pre-policy R&D. This is consistent with Bloom, Schankerman, and Van Reenen's (2013) theoretical finding that the sign of the spillovers on technologically connected firms' R&D is ambiguous.

D.6 Alternative approach to estimating R&D technology spillovers

In this appendix, we discuss a complementary approach to estimating R&D technology spillovers using a monadic specification, following Bloom, Schankerman, and Van Reenen (2013), instead of the dyadic specification discussed in Section 6. We calculate the knowledge spillover pool available to firm *j* as $spilltechR_j = \sum_{i,i\neq j} \omega_{ij} R_i$ where (i) R_i is the average R&D of firm *i* over 2009-11 and (ii) ω_{ij} is the Jaffe (1986) measure of technological "proximity" between firms *i* and *j* (see Appendix D.3), computed based on the distribution of technology classes in which the firms patent. We extend our RD Design approach of using $E_{i,2007}$, firm *i*'s below-assets-threshold indicator, as instrument for R_i to construct $spilltechE_j = \sum_{i,i\neq j} \omega_{ij} E_{i,2007}$ as instrument for $spilltechR_j$. The exclusion restriction requires that the discontinuity-induced random fluctuations in firm i's eligibility would only affect technologically connected firm *j*'s R&D and innovation through R&D spillovers.

Our monadic spillover IV regression estimates the impact of the aggregate R&D spillover pool available to firm *j*, $spilltechR_j$, on firm j's average patents over 2009-13, PAT_j, controlling for firm *j*'s own R&D using $E_{j,2007}$ as an instrument, as specified by the following equation (D4):

[25] Note that due to recent data access constraint, Figure A9 is produced outside of the HMRC Datalab using samples that were built to best replicate the samples used in all the main tables of this paper. Given that R&D data are only available within the Datalab, only patent reduced form results are replicable outside of the Datalab.

$$PAT_j = \alpha + \psi spilltechR_j + F_j(Z_{2007}) + \zeta E_{j,2007} + g\left(z_{j,2007}\right) + \mu techconnect_j + \varepsilon_j$$

where $F_j(Z_{2007}) = \sum_{i,i\neq j} \omega_{ij} f(z_{i,2007})$ and Z_{2007} is a vector comprising of the 2007 assets for all firms; $f(z_{i,2007})$ and $g(z_{j,2007})$ are polynomials of firms i and j's 2007 total assets; and $techconnect_j = \sum_{i,i\neq j} \omega_{ij}$.[26] We instrument $spilltechR_j$ with $spilltechE_j$. $F_j(Z_{2007})$ and $g(z_{j,2007})$ are polynomial controls for $spilltechE_j$ and $E_{j,2007}$ respectively while $techconnect_j$ additionally controls for spillover-receiving firm j's level of "connectivity" in technology space. We estimate the equation (D4) on the sample of firm j's with total assets in 2007 between €51m and €121m. This is a larger bandwidth than in the baseline sample as the policy-induced R&D can have spillovers on firms well beyond the policy threshold.[27] Standard errors are bootstrapped using 1,000 replications over firms.

Column 1 of Table A18 reports the first stage for the R&D spillover term and column 2 the first stage for spillover-receiving firm j's own R&D. As expected the instrument $spilltechE_j$ significantly predicts $spilltechR_j$ (column 1) and the instrument $E_{j,2007}$ significantly predicts connected firm j's own R&D (column 2). The instruments $spilltechE_j$ and $E_{j,2007}$ are jointly statistically different from zero in both columns, with F-statistics of 26.9 and 6.4 respective. Interestingly, we see that in the reduced form patent model of column 3 the R&D spillover instrument, $spilltechE_j$, has a large and significant positive effect on firm j's patents. This is consistent with the hypothesis that policy-induced R&D has sizeable spillover effect on technologically-connected firms' innovation.

Turning to the IV results, column 4 suggests that there is no significant R&D spillover effect on technologically connected firms' R&D, as already suggested by the R&D regression in column 2. By contrast, columns 5 and 6 report that the aggregate R&D spillover pool available to firm j, $spilltechR_j$, *does* have a causal impact on firm j's patenting, consistent with the patent regression in column 3. This spillover effect is robust after controlling for the policy's direct effect on firm j's R&D, either by (i) including $E_{j,2007}$ as a control in addition to the instrumented spillover term (column 5), or (ii) including R_j as a control and using $E_{j,2007}$ as the corresponding instrument (column 6). The latter is a very demanding

[26] Given equation (1) for firm i's R&D as $R_i = \alpha + \beta^R E_{i,2007} + f\left(z_{i,2007}\right) + \varepsilon_i$, aggregating across all firm i's around the SME asset threshold and using ω_{ij} as weights gives:

$$\sum_{i,i\neq j} \omega_{ij} R_i = \alpha \sum_{i,i\neq j} \omega_{ij} + \beta^R \sum_{i,i\neq j} \omega_{ij} E_{i,2007} + \sum_{i,i\neq j} \omega_{ij} f\left(z_{i,2007}\right) + \sum_{i,i\neq j} \omega_{ij}\varepsilon_i$$

$$\Rightarrow spilltechR_j = \alpha techconnect_j + \beta^R spilltechE_j + F_j(Z_{2007}) + \upsilon_j$$

This equation shows that $F_j(Z_{2007})$ is the appropriate polynomial control when using $spilltechE_j$ as instrument for $spilltechR_j$. The key condition that $\nu_j = \sum_{i,i\neq j} \omega_{ij}\varepsilon_i$ is mean independent of $spilltechE_j$ conditional on $F_j(Z_{2007})$ follows from RD Design results. To address non-trivial serial correlation among the error term υ_j, we correct the standard errors using 1,000 bootstrap replications over firms.

[27] Note that $spilltechR_j$ is calculated using the population of all possible firm i's, while $spilltechE_j$ and $F_j(Z_{2007})$ are calculated using all firm i's with 2007 total assets between €51m and €121m (same as the sample on which we nomadic spillover equation), as the RD Design works best in samples of firms around the relevant threshold. Our key results are robust to using different sample bandwidths around the threshold to calculate $spilltechE_j$ and/or to estimate the monadic spillover equation. In addition, in all reported results, we use second order polynomial controls separately on each side of the threshold for $f(z_{i,2007})$ and $g(z_{j,2007})$. In this larger sample we found that higher order terms were significant. However, using different orders of polynomial controls does not change our qualitative findings.

specification, and even though the corresponding spillover coefficient is no longer significant,[28] its magnitude is almost identical in both specifications.

In terms of magnitudes, the last two columns suggest that a £1m increase in R&D by a firm i with an identical technological profile will increase firm j's patenting by 0.014, which is 3.4% of the direct effect of an equivalent R&D increase by the firm itself (= 0.014/0.412). Combining this with the mean level of connectivity among firms in the sample gives us the total spillover effect of 0.616 (= 0.014 x 44). In other words, the total spillovers of an £1m increase in R&D on all technology-connected firms' patenting is about 1.5 times (= 0.616/0.412) the direct effect on own patenting.[29]

This presence of positive R&D spillovers on innovations is robust to a wide range of robustness tests. The reduced-form spillover coefficient capturing effect of $spilltechE_j$ on firm j's patents (column 3's specification) is robust to (i) limiting firm j sample to only patenting firms, (ii) using EPO, UK, and US patent outcomes, (iii) employing the more sophisticated Mahalanobis generalization of the Jaffe proximity measure to allow for between field overlap (see Bloom, Schankerman, and Van Reenen, 2013), (iv) reconstructing the standard Jaffe measure of technological proximity using only information on patents filed up to 2008, and (v) using alternative samples to calculate the instrument $spilltechE_j$ or to estimate the monadic spillover equation.

Besides spillovers in technology space, there may be some negative R&D spillovers through business stealing effects among firms in similar product markets. To address this concern, we follow Bloom, Schankerman, and Van Reenen (2013) and construct $spillsicR_j = \sum_{i,i\neq j} \phi_{ij} R_i$ that captures the aggregate R&D spillovers pool in product market space, where ϕ_{ij} is a measure of product market distance between firms i and j.[30] We also construct $spillsicE_j = \sum_{i,i\neq j} \phi_{ij} E_{j,2007}$ as instrument for $spillsicR_j$. We found no significant effects of $spillsicR_j$ on either firm j's R&D or firm j's patents.

In summary, these findings provide evidence that policy-induced R&D have sizable positive impacts on not only R&D performing firms but also other firms in similar technology areas, as measured by patents. This further supports the use of R&D subsidies in the UK context.

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[28] If we use robust standard errors instead of bootstrapped standard errors, the estimated coefficient (standard error) for $spilltechR_j$ from column 6's specification is 0.014 (0.007), statistically significant at 5% level.

[29] Consider a firm i that increases its R&D by £1m. The spillover of this R&D increase on a firm j's patenting, as estimated by the monadic spillover equation, is $\psi\omega_{ij}$. Summing this spillover over all spillover-receiving firms j' patenting gives total spillovers of $\psi \sum_{j,j\neq i} \omega_{ij} = \psi techconnect_i$, which is the product of the spillover coefficient and firm i's level of connectivity. The estimated total spillover effect for an average firm i is then $\widehat{\psi}\, \overline{techconnect_i} = 0.014 \times 44 = 0.616$.

[30] $\phi_{ij} = 1$ if firm i operates in the same industry as firm j and $\phi_{ij} = 0$ otherwise. To calculate ϕ_{ij}, we use firms' primary industry codes at three-digit SIC level. These data are available from FAME.

Appendix E: Magnitude of effects and tax-price elasticities

E.1 A simple model of patents and R&D demand

Consider a CES production function in R&D capital (G) and non-R&D capital (Z). If input markets are competitive, we can write the long-run static first order condition for factor demand of the firm as:

$$\ln G = -\sigma \ln \rho + \sigma \ln U + \ln Z + B \tag{E1}$$

where ρ is the user cost of R&D capital, U is is the user cost of non-R&D capital and B is a technological constant reflecting factor bias terms in the production function. Assume that G can be described by the perpetual inventory formula $G_t = (1-\delta)G_{t-1} + R_t$ where R is the R&D expenditure in period t. Since in steady state, the R&D just offsets the depreciated part of the R&D stock $\delta G = R$, we can re-write the first order condition in steady state as:

$$\ln R = -\sigma \ln \rho + \sigma \ln U + \ln Z + \ln \delta + \mathrm{B}. \tag{E2}$$

This is essentially the equation we estimate in equation (1).

We also consider a knowledge production function:

$$\ln PAT = \mu + \alpha \ln G. \tag{E3}$$

Substituting the R&D first order condition into this "structural" patent equation generates our key reduced form patent equation:

$$\ln PAT = -\alpha\sigma \ln \rho + \alpha \ln Z + \alpha\sigma \ln U + \alpha \ln \delta + \alpha\mathrm{B} - \mu. \tag{E4}$$

This is essentially what we estimate in equation (2). Around the R&D SME threshold the user cost of non-R&D capital and technology are assumed to be smooth. Non-R&D capital (assets) is the running variable so we have a polynomial approximation to $\ln Z$.

The main departure from the R&D and patent equations above is that the presence of firms with zero patents and/or R&D means we cannot take logarithms. Therefore, we use levels instead of logs as dependent variables. To obtain the logarithmic (proportional) changes we use the empirical averages of the dependent variable in the pre-policy period. We also show that the calculations are robust to using a Poisson regression whose first moment is the exponential log-link function and so is equivalent to estimating in logarithms.

E.2 Estimating the instrument's sharpness using a subsample

Our approach is a fuzzy RD Design. Equations (1) and (3) are the first stage and structural form of a knowledge (patent) production function. But as discussed in subsection 7.2 we may also be interested in the elasticity of R&D with respect to its tax-adjusted use cost. To do this we need to scale the estimate in equation (1) by the "sharpness" of the IV. Consider equation (6):

$$SME_i = \alpha_6 + \lambda E_{i,2007} + f_6\left(z_{i,2007}\right) + \varepsilon_{6i}.$$

Recall that $E_{i,2007}$ is a binary indicator of firm i's being below the new assets threshold in 2007 and SME_i is a binary indicator of the firm's true SME eligibility (which is observable only for R&D performing firms).

Let $\lambda_E = \Pr(SME = 1|E, Z)$ for $E \in \{0,1\}$ in the *full baseline sample* of both R&D performing and non-R&D performing firms. For the sharpness of $E_{i,2007}$ as an instrument for firm's SME-scheme eligibility, we would like to estimate $\lambda \equiv \lambda_1 - \lambda_0$. The problem is that we only observe SME_i for the subsample of R&D performing firms as (a) this data is not in HMRC datasets for non-R&D performers and (b) we cannot calculate eligibility status with precision from the accounting variables. Thus, we can only estimate equation (6) on the R&D performers subsample. Under the RD Design identification assumptions discussed in Section 3, the resulting $\widehat{\lambda}$ from this regression is a consistent estimate for $\tilde{\lambda} \equiv \widetilde{\lambda_1} - \widetilde{\lambda_0}$, where $\widetilde{\lambda_E} = \Pr(SME = 1|E, Z, R > 0)$ for $E \in \{0,1\}$. When will $\tilde{\lambda}$ be equal to λ? We will prove that a sufficient condition for this is that SME-scheme eligibility does not change firm's likelihood of performing R&D, which is something we test (and find empirical support for) in the data.

Let p_S and p_L are the probabilities a firm will perform R&D if it is eligible for the SME scheme (p_S), and if it is not (p_L), and $\rho \equiv p_S/p_L$. Note that by RD Design, we can assume that p_S (and p_L) is the same for firms just below and above the threshold. In the subsample of R&D performing firms, we then have:

$$\widetilde{\lambda_E} = \Pr(SME = 1|E, Z, R > 0) = \frac{\lambda_E p_S}{\lambda_E p_S + (1 - \lambda_E) p_L}.$$

Expanding and rearranging $\widetilde{\lambda_1} - \widetilde{\lambda_0}$ gives:

$$\widetilde{\lambda_1} - \widetilde{\lambda_0} = (\lambda_1 - \lambda_0) \frac{p_S p_L}{[\lambda_1 p_S + (1 - \lambda_1) p_L][\lambda_0 p_S + (1 - \lambda_0) p_L]}$$

$$\Rightarrow \tilde{\lambda} = \lambda \frac{\rho}{(\lambda_1 \rho + 1 - \lambda_1)(\lambda_0 + 1 - \lambda_0)} = \lambda \left\{ 1 + \frac{(\rho - 1)[(1 - \lambda_1)(1 - \lambda_0) - \lambda_1 \lambda_0 \rho]}{[1 + \lambda_1(\rho - 1)][1 + \lambda_0(\rho - 1)]} \right\}.$$

When SME-scheme eligibility does not change firm's likelihood of performing R&D $\rho = 1$ (i.e., $p_S = p_L$). In this case $\tilde{\lambda} = \lambda$. Panel A of Table A7 shows that the policy does not appear to increase firm's participation in R&D performance, suggesting that $p_S \approx p_L$ or $\rho \approx 1$ holds in our setting. This implies that $\tilde{\lambda} \approx \lambda$ in a first-order approximation (as $\frac{(\rho-1)[(1-\lambda_1)(1-\lambda_0) - \lambda_1 \lambda_0 \rho]}{[1+\lambda_1(\rho-1)][1+\lambda_0(\rho-1)]} \approx 0$).

Some additional comments. First, formally the regressions in Panel A of Table A7 estimate $\Delta_p = \Pr(R > 0|E = 1, Z) - \Pr(R > 0|E = 0, Z) = [\lambda_1 p_S + (1 - \lambda_1) p_L] - [\lambda_0 p_S - (1 - \lambda_0) p_L] = (\lambda_1 - \lambda_0)(p_S - p_L)$. $\Delta_p = 0$ implies that $p_S - p_L = 0$ under the reasonable assumption that $\lambda_1 - \lambda_0 > 0$. In addition, Table A8 provides further evidence that the policy effect on R&D is entirely driven by pre-policy R&D performing firms, whose decisions to engage in R&D performance in the pre-policy period did not depend on their post-policy SME status.

Second, note that although $p_S = p_L$ is a sufficient condition, it is not a necessary condition. $\tilde{\lambda} = \lambda$ also if (i) $\lambda = 0$, (ii) $\lambda_1 = 1$ and $\lambda_0 = 0$ (or vice versa), or (iii) $\rho = \frac{(1-\lambda_1)(1-\lambda_0)}{\lambda_1 \lambda_0}$.

Finally, consider the sign of the second-order bias when ρ is not exactly 1. If $\rho > 1$, the sign of the bias depends on $(1 - \lambda_1)(1 - \lambda_0) - \lambda_1 \lambda_0 \rho$, which can be either negative or positive. When $\lambda_1 + \lambda_o \geq 1$ (i.e., sufficiently large share of SME firms in the full baseline sample), $(1 - \lambda_1)(1 - \lambda_0) \leq \lambda_1 \lambda_0 < \lambda_1 \lambda_0 \rho$, implying that the bias is negative. When $\lambda_1 + \lambda_o < 1$, the bias could still be either negative or positive.

E.3 Tax-adjusted user cost of R&D

We calculate the tax-adjusted user cost ρ_f based on the design of the R&D Tax Relief Scheme:

$$\rho_f = \frac{\left(1 - A_f\right)}{\left(1 - \tau_f\right)}(r + \delta)$$

where (i) subscript $f \in \{SME, LCO\}$ denotes whether the firm is a smaller (*SME*) or larger company (*LCO*), (ii) A is the value of R&D tax relief, (iii) τ is the effective corporate tax rate, (iv) r is the real interest rate, and (v) δ is the depreciation rate. We calculate *A* separately for the deduction regime and the payable credit regime using the policy parameters, then derive the average value of *A* using the probability that a baseline sample firm falls into each regime. In the deduction case, $A_{d,f} = \tau_f(1 + e_f)$ where e_f is the enhancement rate. In the payable credit case, $A_c = c(1 + e)$ where c is the payable tax credit rate. Finally, we use the share of baseline firms with corporate tax liabilities over 2006-07 as a proxy for the probability that a baseline firm falls into the deduction regime.

The full formula for tax-adjusted user cost of R&D is then as follows:

$$\rho_f = \left\{ \Pr(Has\ tax\ liability) \times \frac{\left[1 - \tau\left(1 + e_f\right)\right]}{(1 - \tau)} + \Pr(No\ tax\ liability) \times \left[1 - c_f(1 + e_f)\right] \right\} \times\ (r +\ \delta).$$

Note that as the design of the R&D Tax Relief Scheme changes, ρ_f also varies over time with τ, e_f, and c_f.

For simplicity, we do not consider the possibility that a loss-making large company may still benefit from R&D tax relief by carrying the "enhanced" loss forward to future years to reduce its taxable income, as this reduction is only meaningful if the company makes enough profits in this next period. This simplification may overestimate large companies' tax-adjusted user cost of R&D and thereby underestimate the R&D tax-price elasticity (by overestimating the difference in tax-adjusted user cost of R&D between SMEs and large companies). We also do not consider combination claims (cases in which an SME combines tax deduction with the payable tax credit) as there are almost none of them in our baseline sample.

The evolution of tax adjusted user costs of R&D for SMEs and large companies over time is summarized in Table A2. For large companies (for which the payable credit rate is always zero), there are slight decreases in the corporate tax rate over 2006-12 (from 30% to 28% to 26%) coupled with slight increases in the enhancement rate (from 25% to 30%) over the same period. This resulted in a relatively stable tax-adjusted user cost of 0.190 throughout this period. It is therefore reasonable to use the baseline sample's average R&D over 2006-08 as a proxy for how much an average firm in the baseline sample would spend on R&D if it remained a large company over 2009-11, after the policy change. For SMEs, large increases in enhancement rate (from 50% to 75% to 100%) more than offset the slight decrease in corporate tax rate and payable credit rate (from 16% to 14% to 12.5%), leading to a steady reduction in SMEs' tax-adjusted user cost of R&D from 0.154 in 2006 to 0.141 in 2011. This widens the difference in tax-adjusted user cost of R&D between SMEs and large companies over time, from an average percentage difference of -0.218 over 2006-08 to an average percentage difference of -0.269 over 2009-11.

Finally, as a robustness check, we also consider using the small firm profit rate (from 19% to 21% to 20% over 2006-11) instead of the main rate for corporate tax rate. As the tax deduction is less generous with a lower corporate tax rate, the resulting tax-adjusted user cost in the tax deduction case is higher for both SMEs and large companies and their gap is smaller in magnitude (average percentage difference over 2006-08 is -0.185 and over 2009-11 is -0.228).

E.4 Tax-price elasticities of R&D and patents

Some comments on our elasticity estimation. We define elasticity as the percentage difference in R&D (patents) with respect to the percentage difference in the tax-adjusted user cost of R&D. First, given the large policy-induced R&D (patents) increase in our setting, calculating the percentage difference relative to one end point vs. the other end point yields very different results as the difference between the two points is large. We thus focus on the arc elasticity measure, which calculates the percentage difference relative to the midpoint instead of either end points. We also consider alternative elasticity definition using log difference instead of percentage difference (row 2 of Table A18) as discussed below.

Second, as described in subsection 7.2, we derive the elasticity estimate as $\frac{E(\Delta R_i)}{E(\Delta \rho_i)}$, instead of $E\left(\frac{\Delta R_i}{\Delta \rho_i}\right)$ as is standard in the literature. This is because we do not observe SME_i and thereby the implied ρ_i for non-R&D-performing firms. In the sample, it is expected that financially constraint firms have larger elasticities, and are also more likely to experience larger reduction in tax-adjusted user costs of R&D. This positive correlation implies that $\left|\frac{E(\Delta R_i)}{E(\Delta \rho_i)}\right| > \left|E\left(\frac{\Delta R_i}{\Delta \rho_i}\right)\right|$.

Finally, to derive the empirical distributions and confidence intervals of our elasticity estimators, we perform a bootstrap procedure with 1,000 replications. In each replication, we draw observations with replacement from the baseline sample and calculate the elasticities based on the resulting regression estimates and sample means. As the first-stage estimate of the effect of firm's below-assets-threshold indicator on its post-policy SME status is based on a smaller sample of 361 R&D performing firms, we separately draw 361 observations from this subsample and 5,527 (= 5,888 - 361) observations from the remaining subsample. Drawing from the full sample without separating the subsamples yields quantitatively similar distributions.

Tax-price elasticities of patents. Combining $\hat{\beta}^{PAT}$ = 0.042 (column 15 of Table 4) with $\hat{\lambda}$ = 0.353 (column 5 of Table 9) gives a patent treatment effect (of the more generous SME scheme) of 0.119 (= 0.042/0.353). This treatment effect and the pre-policy mean patents of 0.064 imply a patent percentage difference of $\frac{PAT_{SME}-PAT_{LCO}}{(PAT_{SME}+PAT_{LCO})/2} = \frac{0.119}{(0.119+0.064+0.064)/2} = 0.96$. This then yields a patent elasticity with respect to R&D tax-adjusted user cost of 3.6 (= 0.96/0.27). Similarly, using $\hat{\beta}^{PAT}$ estimated from the subsample of R&D performers used to estimate $\hat{\lambda}$ yields an elasticity of patents with respect to R&D user cost of 2.9 (see Table A18, rows 7 for details).

Appendix F: Macro aspects of the R&D Tax Relief Scheme

A full welfare analysis of the R&D Tax Relief Scheme requires both an analysis of the benefits in terms of (say) the increased GDP generated by the R&D induced by the policy (including spillovers) and the deadweight cost of taxation. We would also need to take a position on other general equilibrium effects such as the increase in the wages of R&D workers due to increased demand (Goolsbee, 1998). As an interim step towards this we follow the convention in the literature which is to calculate a "value for money" ratio $\mu \equiv \frac{\Delta_R}{\Delta_{EC}}$ where Δ_R is the amount of R&D induced by the policy and Δ_{EC} is the total amount of additional taxpayer money needed to pay for the scheme (which we call "Exchequer Cost", EC).

We consider three policy-relevant experiments. First, we look at the 2008 extension of the SME Scheme. Second, we do a "value for money" calculation in our data period 2006-11. Finally, we do a simulation of what the path of UK business R&D to GDP would have been with and without the R&D Tax Relief Scheme.

F.1 2008 extension of the SME Scheme

With respect to the 2008 extension of the SME Scheme to cover "larger" SMEs, Δ_R measures the increase in R&D induced by more generous tax relief under the SME Scheme by a firm benefitting from the scheme thanks to the new thresholds. That is, $\Delta_R = R_{new} - R_{old}$ where R_{new} and R_{old} are the firm's R&D's under the new and old policies respectively. Similarly, $\Delta_{EC} = EC_{new} - EC_{old}$ where EC_{new} and EC_{old} are the firm's corresponding Exchequer costs due to the policy change.

Rearranging the R&D tax-price elasticity formula gives:

$$\eta = \frac{\frac{R_{new} - R_{old}}{(R_{new} + R_{old})/2}}{\frac{\rho_{new} - \rho_{old}}{(\rho_{new} + \rho_{old})/2}} = \frac{\Delta_R / \bar{R}}{\Delta_\rho / \bar{\rho}} \Rightarrow \frac{\Delta_R}{\bar{R}} = \eta \times \frac{\Delta_\rho}{\bar{\rho}}$$

where ρ is the tax-adjusted user cost of R&D, $\Delta_X \equiv X_{new} - X_{old}$, and $\overline{X} \equiv (X_{new} + X_{old})/2$. For simplicity, we consider the tax deduction case and the SME payable tax credit case separately.

SME tax deduction case. In this case,

$$\rho^{deduction} = \frac{\big(1 - \tau(1 + e)\big)}{1 - \tau}(r + \delta)$$

$$EC^{deduction} = R \times e \times \tau$$

where τ is the effective corporate tax rate, e is the enhancement rate, r is the real interest rate, and δ is the depreciation rate. As the above firm moves from being a large company pre-2008 to being an SME post-2008, its enhancement rate increases from 25% to 75%. At the same time, corporate tax rate decreases from 30% to 28%. Combining $e_{old} = 0.25, e_{new} = 0.75, \tau_{old} = 0.30, \tau_{new} = 0.28$ with estimated R&D tax-price elasticity of $\eta = -4.0$ gives $\frac{\Delta_\rho}{\bar{\rho}} = -0.23$ and $\frac{\Delta_R}{\bar{R}} = 0.92$, which implies $\frac{R_{new}}{R_{old}} = 2.70$.

On the cost side, we have:

$$EC_{old} = R_{old} \times e_{old} \times \tau_{old} = R_{old} \times 0.075,$$

$$EC_{new} = R_{new} \times e_{new} \times \tau_{new} = R_{new} \times 0.21.$$

Putting all the elements together gives:

$$\mu^{deduction} \equiv \frac{\Delta_R}{\Delta_{EC}} = \frac{R_{new} - R_{old}}{EC_{new} - EC_{old}} = \frac{(R_{old} \times 2.70) - R_{old}}{(R_{old} \times 2.70 \times 0.21) - (R_{old} \times 0.075)} = \frac{1.70}{0.49} = 3.46.$$

That is, the value for money ratio in the SME tax deduction case is 3.46. In other words, £1 of taxpayer money generates £3.46 in additional R&D.

Finally, note that Δ_{EC} could be rewritten as:

$$\Delta_{EC} = EC_{new} - EC_{old} = R_{new} \times 0.21 - R_{old} \times 0.075 = \Delta_R \times 0.21 + R_{old} \times (0.21 - 0.075)$$

where the first element represents the Exchequer costs associated with new R&D and the second term reflects additional Exchequer costs paid on existing R&D due to more generous tax relief. In this case, the majority of the additional costs are because of the new R&D generated, i.e., $\Delta_R \times 0.21 = R_{old} \times 0.36$ makes up close to 73% of Δ_{EC} ($\Delta_{EC} = R_{old} \times 0.49$).

SME payable tax credit case. In this case,

$$\rho^{credit} = (1 - c(1 + e))(r + \delta)$$

$$EC^{credit} = R \times c \times (1 + e)$$

where c – the payable credit rate – is always zero for large companies and 14% for SMEs post-2008. Combining $c_{old} = 0, c_{new} = 0.14, e_{old} = 0.25, e_{new} = 0.75$, and $\eta = -4.0$ gives $\frac{\Delta_\rho}{\bar{\rho}} = -0.28$ and $\frac{\Delta_R}{\bar{R}} = 1.11$, which implies $\frac{R_{new}}{R_{old}} = 3.51$. On the cost side, $EC_{old} = 0$ and $EC_{new} = R_{new} \times c_{new} \times (1 + e_{new}) = R_{new} \times 0.25$. Putting all the elements together gives:

$$\mu^{payable} \equiv \frac{\Delta_R}{\Delta_{EC}} = \frac{R_{new} - R_{old}}{EC_{new} - EC_{old}} = \frac{R_{old} \times 3.51 - R_{old}}{R_{old} \times 3.51 \times 0.25 - 0} = \frac{2.51}{0.86} = 2.92.$$

The value for money ratio in the payable tax credit case is 2.92. In this case, the amount of additional R&D's Exchequer costs due to newly-generated R&D $\Delta_R \times 0.25 = R_{old} \times 0.62$ constitutes close to 72% of Δ_{EC} ($\Delta_{EC} = R_{old} \times 0.82$).

F.2 R&D Tax Relief Scheme over 2006-11

To evaluate the overall R&D Tax Relief Scheme over 2006-11, we calculate:

$$\mu \equiv \frac{\Delta_R}{\Delta_{EC}} = \frac{R_{tax\ relief} - R_{no\ tax\ relief}}{EC_{tax\ relief} - EC_{no\ tax\ relief}} = \frac{R_{taxrelief} - R_{no\ tax\ relief}}{EC}$$

separately for each of three sub-schemes, SME tax deduction scheme (Panel B of Table A20), SME payable tax credit scheme (Panel C), and large company tax deduction scheme (Panel D), in each year, using the same approach as described in detail above. We generalize our estimated tax-price elasticity of 4.0 to the whole population of SMEs, but use a lower-bound tax-price elasticity of 1.1 for the population of large companies as these firms are less likely to be credit constrained and therefore less responsive to tax incentives. In addition, we use the small profits rate (19%-21%) instead of the regular corporate tax rate

(26%-30%) for the population of SMEs as most of them are much smaller than the "larger" SMEs in our baseline sample and therefore most likely qualify for the small profits rate.

As reported in Table A20, the SME tax deduction's value for money ratio decreases from 4.2 in 2006 to 3.6 in 2011 as SME tax deduction becomes significantly more generous over time. On the other hand, SME payable tax credits and large company tax deduction's value for money ratios are stable at around 2.9 and 1.5 respectively as these schemes do not change much over this period. The fact that all the value for money ratios are well above unity indicates that the R&D Tax Relief Scheme is effective in inducing additional R&D at relatively low cost to the Exchequer.

Finally, we estimate the amount of additional R&D induced by the R&D Tax Relief Scheme as $\Delta_R = \mu \times EC$ using the calculated value for money ratios μ's and Exchequer costs national statistics (HMRC 2015). We do this for each of the three schemes in each year in Panels B, C and D, and then aggregate them together in Panel E.

To give an example, consider the SME tax deduction scheme in Panel B for 2009. The tax-adjusted user cost of R&D under this sub-scheme in 2009, calculated using the policy parameters, is $\frac{1-0.21\times(1+0.75)}{1-0.21}(0.05+0.15) = 0.16$. The counterfactual user cost in world without R&D tax relief is $0.05 + 0.15 = 0.20$ $(e = 0)$. The percentage difference between these user costs is then $\frac{\Delta_\rho}{\overline{\rho}} = \frac{0.16-0.20}{(0.16+0.20)/2} = -0.22$. The tax-price elasticity of R&D of SMEs as estimated in subsection 7.2 is $\eta^{SME} = -4.0$.

The elasticity formula and Exchequer cost formulae give:

$$\eta^{SME} = \frac{\Delta_R / \overline{R}}{\Delta_\rho / \overline{\rho}} \Rightarrow \Delta_R = \overline{R} \times \eta^{SME} \times \frac{\Delta_\rho}{\overline{\rho}}$$

$$\Delta_{EC} = EC_{tax\,relief} - 0 = R_{tax\,relief} \times e \times \tau = \left(\overline{R} + \frac{\Delta_R}{2}\right) \times e \times \tau = \overline{R} \times \left(1 + 0.5 \times \frac{\Delta_R}{\overline{R}}\right) \times e \times \tau$$

$$\Rightarrow \mu^{SME\,deduction} = \frac{\Delta_R}{\Delta_{EC}} = \frac{\eta^{SME} \times \frac{\Delta_\rho}{\overline{\rho}}}{\left(1 + 0.5 \times \frac{\Delta_R}{\overline{R}}\right) \times e \times \tau} = \frac{4.0 \times 0.22}{(1 + 0.5 \times 4.0 \times 0.22) \times 0.75 \times 0.21} = 3.89.$$

We report this value for money ratio in the second row of Panel B of Table A20.[31] From HMRC data we know that £130m was paid out in the SME deduction in this year. Hence, we can calculate that the total amount of additional R&D induced $\Delta_R = \mu^{SME\,deduction} \times EC = 3.89 \times 130 = 506$ (£m), as shown in fourth row of Panel B.

As discussed in subsection 7.3, our aggregate estimates in Panel E suggest that the overall impact of the R&D Tax Relief Scheme is large. Over 2006-11, the policy, which costs less than £6 billion in lost tax

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[31] To be consistent with how policy tax-payer costs are reported in HMRC data, we calculate these value-for-money ratios without accounting for pre-enhancement lost tax revenue from policy-induced R&D. If we also include this amount into tax-payer costs, the respective value-for-money ratios of the three schemes are 2.2, 2.9, and 1.1, and the aggregate value-for-money ratio of the whole R&D Tax Relief Scheme over 2006-11 is 1.5.

revenue, induced close to £12 billion in additional R&D. *On an annualized basis, spending £0.96 billion produced £1.98 billion of additional R&D.*

These calculations show our estimates of what the counterfactual path of R&D would have been in the absence of the R&D Tax Relief Scheme. The bottom row of Table A20 gives the yearly breakdown. For example, the final column shows that on average 2006-11 we estimate that R&D would be a full 20% lower in the absence of the tax scheme.

F.3 Counterfactual R&D without the Tax Relief Scheme 2000-11

It is important to note that throughout our analysis we have been focusing on *qualifying* R&D, i.e., that part of business R&D that is eligible for tax relief. Aggregate qualifying R&D is lower than the figures for Business Enterprise R&D (BERD) reported in Figure 5. For example, in 2011 aggregate BERD was £17bn and aggregate qualifying R&D was £12bn. There are various reasons for this difference, including the fact that BERD includes R&D spending on capital investment whereas qualified R&D does not (only current expenses are liable). It is also the case that HMRC defines R&D more narrowly for tax purposes that BERD which is based on the Frascati definition.

We present counterfactual BERD to GDP ratios in Figure 5. To calculate the counterfactual (the dotted line "UK without tax relief" in Figure 5) we simply deduct the additional qualified R&D that we estimate were created by the R&D tax relief system (second row of Panel E of Table A20) from the aggregate BERD numbers from OECD MSTI Dataset (https://stats.oecd.org/Index.aspx?DataSetCode=MSTI_PUB). Since BERD is greater than qualifying R&D, the 20% fall in qualifying R&D translates into a 13% fall in BERD.

Table A1. Design of UK R&D Tax Relief Scheme, 2000-12

Effective from		SME ceilings: Employment	SME ceilings: Total assets	SME ceilings: Turnover	Enhancement: SME	Enhancement: Large company	Payable credit: SME	Payable credit: Large company	Effective for
2000	April	249	€27m	€40m	50%	0%	16%	0%	Expenditure that incurred on or after April 1st, 2000
2002	April	"	"	"	"	25%	"	"	Expenditure that incurred on or after April 1st, 2002
2005	January	"	€43m	€50m	"	"	"	"	Accounting period that ended on or after January 1st, 2005
2008	**April* August***	**499**	**€86m**	**€100m**	**75%**	**30%**	**14%****	**"**	LCOs: expenditure that incurred on or after April 1st, 2008 SMEs: expenditure that incurred on or after August 1st, 2008
2011	April	"	"	"	100%	"	12.5%**	"	Expenditure that incurred on or after April 1st, 2011
2012	April	"	"	"	125%	"	"	"	Expenditure that incurred on or after April 1st, 2012

Note: To be considered an SME, a company must not exceed the employment ceiling and either the total assets ceiling or the sales ceiling. The measurements and account aggregation rules for employment, total assets, and sales are set according to 1996/280/EC (up to 2004) and 2003/361/EC (from 2005), yet the ceiling increase in 2008 applied only to the R&D Tax Relief Scheme. A company loses (acquires) its SME status if it fails (passes) the ceiling tests over two consecutive accounting periods (two-year rule). An SME working as subcontractor for a large company can only claim under the Large Company Scheme. From April 2000 to March 2012, there was a minimum requirement of £10,000 in qualifying R&D expenditure for both SMEs and large companies. * Enhancement rate increase for large companies became effective on April 1st, 2008. Changes in SME ceilings and enhancement and payable credit rates under the SME scheme became effective on August 1st, 2008. ** The reductions in payable credit rate is to ensure that effective state aid intensity does not exceed the limit of 25% imposed by the European Commission.

Table A2. Tax-adjusted user cost of R&D capital over time

Tax relief scheme	(1) SME: Deduction	(2) SME: Payable credit	(3) SME: Average	(4) Large company: Deduction	(5) Large company: Payable credit	(6) Large company: Average	(7) **Arc % difference user cost**	(8) **Log difference user cost**
2006	0.157	0.152	0.154	0.179	0.200	0.190	-0.209	-0.210
2007	0.157	0.152	0.154	0.179	0.200	0.190	-0.209	-0.210
2008	0.147	0.151	0.149	0.177	0.200	0.190	-0.237	-0.238
2009	0.142	0.151	0.147	0.177	0.200	0.190	-0.254	-0.255
2010	0.142	0.151	0.147	0.177	0.200	0.190	-0.254	-0.255
2011	0.130	0.150	0.141	0.179	0.200	0.191	-0.300	-0.302
2006-2008	0.154	0.152	0.153	0.178	0.200	0.190	-0.218	-0.219
2009-2011	**0.138**	**0.151**	**0.145**	**0.177**	**0.200**	**0.190**	**-0.269**	**-0.271**

Note: Tax-adjusted user cost of R&D capital is calculated using formulae as described in subsection 7.2. Corporate tax rate is 30% in 2006-2007, 28% in 2008-2010, and 26% in 2011. Enhancement rate is 50% for SMEs and 25% for large companies in 2006-2008, 75% for SMEs and 30% for large companies in 2008-2010, 100% for SMEs and 30% for large companies in 2011. Payable credit rate is 16% in 2006-2008, 14% in 2008-2010, and 12.5% in 2011. Share of the payable credit case is 55%. Real interest rate is 5%. Depreciation rate is 15%.

Table A3. Effects on R&D and patents among firms below and above SME employment threshold

Panel A. Firms with 2007 employment not exceeding 499

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
Dependent variable	**R&D exp. *(£ '000)***			**All patent family count**						
	Before	3 years After		Before	3 years After		5 years After		7 years After	
Year	2006-08 avg.	2009-11 avg.	3yr difference	2006-08 avg.	2009-11 avg.	3yr difference	2009-13 avg.	5yr difference	2009-15 avg.	7yr difference
Below-assets-threshold in 2007	3.1	156.3*	153.2**	0.039	0.147**	0.108**	0.123**	0.084*	0.105**	0.066
	(92.4)	(82.6)	(76.3)	(0.056)	(0.064)	(0.049)	(0.051)	(0.045)	(0.046)	(0.45)
Dependent variable mean (same period)	*96.6*	*120.8*		*0.098*	*0.100*		*0.094*		*0.089*	
Firms	2,246	2,246	2,246	2,246	2,246	2,246	2,246	2,246	2,246	2,246

Panel B. Firms with 2007 employment above 499

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
Dependent variable	**R&D exp. *(£ '000)***			**All patent family count**						
	Before	3 years After		Before	3 years After		5 years After		7 years After	
Year	2006-08 avg.	2009-11 avg.	3yr difference	2006-08 avg.	2009-11 avg.	3yr difference	2009-13 avg.	5yr difference	2009-15 avg.	7yr difference
Below-assets-threshold in 2007	374.5*	394.3	19.8	0.095	0.110	0.015	0.114	0.019	0.127	0.032
	(218.3)	(216.3)	(84.7)	(0.121)	(0.104)	(0.061)	(0.110)	(0.065)	(0.100)	(0.068)
Dependent variable mean (same period)	*235.9*	*266.6*		*0.150*	*0.124*		*0.126*		*0.117*	
Firms	845	845	845	845	845	845	845	845	845	845

Note: OLS estimates are based on the RD Design in equations (1) and (2). The running variable is total assets in 2007 with a threshold of €86m. Baseline sample includes firms with total assets in 2007 within €25m of the threshold (i.e., between €61m and €111m). Controls include first order polynomials of the running variable separately for each side of the threshold. Robust standard errors are in brackets. **Panel A** considers the subsample of firms with 2007 employment not exceeding the new SME threshold of 499. **Panel B** considers the subsample of firms with 2007 employment above the new SME threshold of 499. Firms with missing 2007 employment are not included in either subsamples.

*** denotes statistical significance at the 1% level, ** 5% level, * 10% level.

Table A4. R&D regression robustness tests

Panel A.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
Dependent variable	**R&D expenditure, 2009-11 average *(£ '000)***									
Specification	Higher order polynomial controls		Alternative kernel weight		Alternative bandwidth around the assets threshold					
Below-assets-threshold in 2007	189.9**	186.2*	144.0***	150.0**	182.8**	143.4**	204.2***	186.0***	121.0**	95.7**
	(84.7)	(108. 3)	(55.5)	(58.9)	(71.3)	(56.3)	(72.5)	(67.5)	(52.5)	(47.3)
Polynomial controls	2^{nd}	3^{rd}	1^{st}	1^{st}	1^{st}	1^{st}	2^{nd}	2^{nd}	1^{st}	1^{st}
Kernel weight			Epa	Tri					Tri	Tri
Bandwidth (€m)	25	25	25	25	15	20	30	35	30	35
Firms	5,888	5,888	5,888	5,888	3,394	4,615	7,255	8,818	7,255	8,818

Panel B.

	(11)	(12)	(13)	(14)	(15)	(16)	(17)	(18)	(19)	(20)
Dependent variable	**R&D expenditure, 2009-11 average *(£ '000)***									
Specification	Industry & location fixed effects			Alternative winsorization parameter			Alt. LDV	CCT	Poisson	Neg. Bin.
Below-assets-threshold in 2007	106.9*	121.7**	103.6**	156.9**	87.3**	43.5*	60.8*	190.0***	1.31***	1.22**
	(57.2)	(52.0)	(52.2)	(64.6)	(38.6)	(25.0)	(33.9)	(74.8)	(0.49)	(0.49)
Fixed effects	Ind.	Loc.	Ind. x Loc.							
Year of LDV							2007			
Bandwidth (€m)								20		
Winsorized window	2.5%	2.5%	2.5%	1.0%	5.0%	No outliers	2.5%	2.5%	2.5%	2.5%
Firms	4,504	5,868	4,498	5,888	5,888	5,872	5,888	4,859	5,888	5,888

Note: OLS estimates are based on the RD Design in equation (1). The running variable is total assets in 2007 with a threshold of €86m. Baseline sample includes firms in 2007 within €25m of the threshold (i.e., between €61m and €111m). Controls include first order polynomials of running variable separately for each side of the threshold. Robust standard errors are in brackets.

Panel A: Columns (1) and (2) control for second or third order polynomials of running variable. The coefficients on the second and third order assets terms are not statistically significant. Columns (3) and (4) use Epanechnikov or triangular kernel weights. Columns (5) and (6) use samples with smaller bandwidths around the threshold, also controlling for first order polynomial of the running variable. Columns (7)-(10) use samples with larger bandwidths around the threshold. Columns (7) and (8) control for second order polynomial of the running variable to improve the fit (the coefficients on the second order assets terms are statistically significant for larger bandwidths). Columns (9) and (10) control for first order polynomial of the running variable and use triangular kernel weights.

Panel B: Columns (11)-(13) add industry (four-digit SIC), location (two-digit postcode), and industry x location (two-digit SIC x one-digit postcode) fixed effects. Columns (14)-(16) use samples with different winsorization parameter or sample excluding outliers in R&D expenditure. Column (17) adds R&D expenditure in 2007 as lagged dependent variable control. Column (18) reports Calonico et al.'s (CCT) (2014) robust bias-corrected optimal bandwidth RD estimate using triangular kernel weights. Column (19) and (20) uses Poisson and Negative Binomial specifications instead of OLS, to allow for a proportional effect on R&D (as in a semi-log specification).

*** denotes statistical significance at the 1% level, ** 5% level, * 10% level.

Table A5. Patent regression robustness tests

Panel A.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
Dependent variable	**All patent family count, 2009-13 average**									
Specification	Higher order polynomial controls		Alternative kernel weight		Alternative bandwidth around the assets threshold					
Below-assets-threshold in 2007	0.066	0.056	0.068**	0.067**	0.068	0.061**	0.057	0.091***	0.068***	0.063***
	(0.041)	(0.044)	(0.027)	(0.027)	(0.045)	(0.030)	(0.038)	(0.031)	(0.025)	(0.024)
Polynomial controls	2nd	3rd	1st	1st	1st	1st	2nd	2nd	1st	1st
Kernel weight			Epa	Tri					Tri	Tri
Sample assets (€m)	25	25	25	25	15	20	30	35	30	35
Firms	5,888	5,888	5,888	5,888	3,394	4,615	7,255	8,818	7,255	8,818

Panel B.

	(11)	(12)	(13)	(14)	(15)	(16)	(17)	(18)	(19)	(20)
Dependent variable	**All patent family count, 2009-13 average**									
Specification	Industry & location fixed effects			Alternative winsorization parameter			Alt. LDV	CCT	Poisson	Neg. Bin.
Below-assets-threshold in 2007	0.063*	0.065***	0.061**	0.067**	0.063***	0.070***	0.047**	0.074***	1.29***	1.46***
	(0.034)	(0.025)	(0.024)	(0.027)	(0.024)	(0.026)	(0.022)	(0.029)	(0.46)	(0.47)
Fixed effects	Ind.	Loc.	Ind. x Loc.							
Year of LDV							2007			
Bandwidth (€m)								31.2		
Winsorized window	2.5%	2.5%	2.5%	1.0%	5.0%	No outliers	2.5%	2.5%	2.5%	2.5%
Firms	4,504	5,868	4,498	5,888	5,888	5,872	5,888	7,872	5,888	5,888

Note: OLS estimates are based on the RD Design in equation (2). The running variable is total assets in 2007 with a threshold of €86m. Baseline sample includes firms in 2007 within €25m of the threshold (i.e., between €61m and €111m). Controls include first order polynomials of running variable separately for each side of the threshold. Robust standard errors are in brackets.

Panel A: Columns (1) and (2) control for second or third order polynomials of running variable. The coefficients on the second and third order assets terms are not statistically significant. Columns (3) and (4) use Epanechnikov or triangular kernel weights. Columns (5) and (6) use samples with smaller bandwidths around the threshold, also controlling for first order polynomial of the running variable. Columns (7)-(10) use samples with larger bandwidths around the threshold. Columns (7) and (8) control for second order polynomial of the running variable to improve the fit (the coefficients on the second order assets terms are statistically significant for larger bandwidths). Columns (9) and (10) control for first order polynomial of the running variable and use triangular kernel weights.

Panel B: Columns (11)-(13) add industry (four-digit SIC), location (two-digit postcode), and industry x location (two-digit SIC x one-digit postcode) fixed effects. Columns (14)-(16) use samples with different winsorization parameter or sample excluding outliers in all patent family count. Column (17) adds all patent family count in 2007 as lagged dependent variable control. Column (18) reports Calonico et al.'s (CCT) (2014) robust bias-corrected optimal bandwidth RD estimate using triangular kernel weights. Column (19) and (20) uses Poisson and Negative Binomial specifications instead of OLS, to allow for a proportional effect on R&D (as in a semi-log specification).

*** denotes statistical significance at the 1% level, ** 5% level, * 10% level.

Table A6. Patent IV regression robustness tests

Panel A.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
Dependent variable	**All patent family count, 2009-13 average**									
Specification	Higher order polynomial controls		Alternative kernel weight		Alternative bandwidth around the assets threshold					
R&D expenditure	0.345	0.301	0.475**	0.449**	0.370	0.428*	0.278	0.489**	0.558**	0.655*
(£m), 2009-11 avg.	(0.227)	(0.248)	(0.232)	(0.221)	(0.242)	(0.236)	(0.191)	(0.213)	(0.280)	(0.363)
Polynomial controls	2nd	3rd	1st	1st	1st	1st	2nd	2nd	1st	1st
Kernel weight			Epa	Tri					Tri	Tri
Sample assets (€m)	25	25	25	25	15	20	30	35	30	35
Firms	5,888	5,888	5,888	5,888	3,394	4,615	7,255	8,818	7,255	8,818

Panel B.

	(11)	(12)	(13)	(14)	(15)	(16)	(17)	(18)
Dependent variable	**All patent family count, 2009-13 average**							
Specification	Industry & location fixed effects			Alternative winsorization parameter			LDV control	
R&D expenditure	0.587	0.534*	0.589	0.428*	0.721**	1.597*	0.434*	0.421*
(£m), 2009-11 avg.	(0.435)	(0.304)	(0.411)	(0.224)	(0.355)	(0.939)	(0.243)	(0.251)
Fixed effects	Industry	Location	Ind. x Loc.					
Year of LDV							2006-08 average	2007
Winsorized window	2.5%	2.5%	2.5%	1.0%	5.0%	No outliers	2.5%	2.5%
Firms	4,504	5,868	4,498	5,888	5,888	5,872	5,888	5,888

Note: IV estimates are based on equation (3). Instrumental variable is the indicator whether total assets in 2007 is below €86m. Baseline sample includes firms with total assets in 2007 within €25m of the threshold (i.e., between €61m and €111m). Controls include for first order polynomials of the running variable (total assets in 2007) separately for each side of the threshold. Robust standard errors are in brackets.

Panel A: Columns (1) and (2) control for second or third order polynomials of running variable. Columns (3) and (4) use Epanechnikov or triangular kernel weights. The coefficients on the second and third order assets terms are not statistically significant. Columns (5) and (6) use samples with smaller bandwidths around the threshold, also controlling for first order polynomial of the running variable. Columns (7)-(10) use samples with larger bandwidths around the threshold. Columns (7) and (8) control for second order polynomial of the running variable to improve the fit (the coefficients on the second order assets terms are statistically significant for larger bandwidths). Columns (9) and (10) control for first order polynomial of the running variable and use triangular kernel weights.

Panel B: Columns (11)-(13) add industry (four-digit SIC), location (two-digit postcode), and industry x location (two-digit SIC x one-digit postcode) fixed effects. Columns (14)-(16) use samples with different winsorization parameter or sample excluding outliers in all patent family count. Columns (17) and (18) add average all patent family count over 2006-08 or all patent family count in 2007 as lagged dependent variable control.

*** significant at 1% level, ** 5% level, * 10% level.

Table A7. Additional results on effects of R&D tax relief on quality-adjusted patents

Panel A.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
Dependent variable (2009-13 average)	**Patent count weighted by citations**			**All patent family count weighted by quality index**				**All patent family count in top quality quartile, by**		
	EPO patents	UK patents	US patents	Scaled citation	Scope	Gene-rality	Origi-nality	Scope	Gene-rality	Origi-nality
Below-assets-threshold in 2007	0.013*	0.044*	0.056*	1.729*	0.132**	0.010**	0.030***	0.038***	0.051***	0.036***
	(0.008)	(0.026)	(0.034)	(0.954)	(0.052)	(0.005)	(0.012)	(0.013)	(0.019)	(0.014)
Dependent variable mean over 2006-08	*0.025*	*0.114*	*0.125*	*2.881*	*0.130*	*0.017*	*0.027*	*0.027*	*0.037*	*0.027*
Discontinuity estimate to baseline mean ratio	*0.53*	*0.38*	*0.45*	*0.60*	*1.02*	*0.59*	*1.12*	*1.40*	*1.38*	*1.35*
Firms	5,888	5,888	5,888	5,888	5,888	5,888	5,888	5,888	5,888	5,888

Panel B.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Dependent variable (2009-13 average)	**All patent family count**		**EPO patent count**					
	BTP patents	Non-BTP patents	Chem. patents	Non-chem. patents	BTP patents	Non-BTP patents	ICT patents	Non-ICT patents
Below-assets-threshold in 2007	0.0083**	0.0573**	0.0125**	0.0206*	0.0075**	0.0262*	0.0036*	0.0262**
	(0.0034)	(0.0242)	(0.0059)	(0.0123)	(0.0032)	(0.0146)	(0.0019)	(0.0130)
Dependent variable mean over 2006-08	*0.0030*	*0.0573*	*0.0068*	*0.0211*	*0.0012*	*0.0276*	*0.0015*	*0.0270*
Discontinuity estimate to baseline mean ratio	*2.75*	*1.00*	*1.84*	*0.98*	*6.36*	*0.95*	*2.40*	*0.97*
Firms	5,888	5,888	5,888	5,888	5,888	5,888	5,888	5,888

Note: OLS estimates are based on the RD Design in equation (2). The running variable is total assets in 2007 with a threshold of €86m. Baseline sample includes firms with total assets in 2007 within €25m of the threshold (i.e., between €61m and €111m). Controls include first order polynomials of the running variable separately for each side of the threshold. Robust standard errors are in brackets.

Panel A: Columns (1)-(3) weight EPO patent count, UK patent count, or US patent count by citations. Columns (4)-(7) weight all patent family count by scaled citation (column 4), patent scope (column 5), patent generality index (column 6), or patent originality index (column 7). Scaled citation measures a patent's citations relative to the average citations of patents in the same patent sector x filing office x filing year cell. Patent scope counts the number of four-digit IPC patent classes in which a patent is classified. Generality index measures the patent-class diversity of a patent's forward citations. Originality index measures the patent-class diversity of a patent's backward citations. Columns (8)-(10) count all patent families in the top 25% in quality of their patent field x filing year cohorts, with patent quality measured by patent scope (column 8), generality index (column 9), originality index (column 10).

Panel B: Columns (1) and (2) split all patent counts into biotechnology and pharmaceutical (BTP) patents and non-BTP patents. Column (3)-(8) split EPO patent counts into chemistry/pharmaceutical and non-chemistry/pharmaceutical patents (columns 3 and 4), BTP and non-BTP patents (columns 5 and 6), and ICT and non-ICT patents (column 7 and 8). Chemistry/pharmaceutical patents include all patents classified into patent sector (3) Chemistry. BTP patents include all patents classified into either patent field (11) Analysis of biological materials, (15) Biotechnology, or (16) Pharmaceuticals (i.e., a subset of chemistry/pharmaceutical patents). ICT patents include all patents classified into either patent field (4) Digital communication, (6) Computer technology, or (7) IT methods for management.

*** denotes statistical significance at the 1% level, ** 5% level, * 10% level.

Table A8. Heterogeneous effects of R&D tax relief by BTP and ICT industries

Panel A. Biotechnology and Pharmaceutical (BTP) vs. non-BTP industries

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
Dependent variable	**R&D expenditure (£ *'000*), 2009-11 avg.**		**All patent family count, 2009-13 avg.**		**EPO patent count, 2009-13 avg.**		**UK patent count, 2009-13 avg.**		**US patent count, 2009-13 avg.**	
Subsample	BTP ind.	Non-BTP ind.	BTP ind.	Non-BTP ind.	BTP ind.	Non-BTP ind.	BTP ind.	Non-BTP ind.	BTP ind.	Non-BTP ind.
Below-assets-threshold in 2007	177.0	100.2*	0.116**	0.050*	0.073*	0.021	0.109*	0.064*	0.0600*	0.033*
	(109.3)	(58.0)	(0.057)	(0.029)	(0.039)	(0.016)	(0.062)	(0.036)	(0.0313)	(0.0192)
Dependent variable mean over 2006-08	*105.1*	*61.3*	*0.099*	*0.049*	*0.054*	*0.020*	*0.111*	*0.062*	*0.039*	*0.020*
Discontinuity estimate to baseline mean ratio	*1.68*	*1.64*	*1.17*	*1.01*	*1.34*	*1.05*	*0.98*	*1.04*	*1.53*	*1.65*
Difference	76.8		0.066		0.052		0.045		0.027	
	(123.7)		(0.064)		(0.043)		(0.072)		(0.037)	
Firms	1,709	4,179	1,709	4,179	1,709	4,179	1,709	4,179	1,709	4,179

Panel B. Information and Communication Technology (ICT) vs. non-ICT industries

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
Dependent variable	**R&D expenditure (£ *'000*), 2009-11 avg.**		**All patent family count, 2009-13 avg.**		**EPO patent count, 2009-13 avg.**		**UK patent count, 2009-13 avg.**		**US patent count, 2009-13 avg.**	
Subsample	ICT ind.	Non-ICT ind.	ICT ind.	Non-ICT ind.	ICT ind.	Non-ICT ind.	ICT ind.	Non-ICT ind.	ICT ind.	Non-ICT ind.
Below-assets-threshold in 2007	201.6**	82.3	0.078*	0.0645*	0.062	0.023	0.091*	0.070*	0.060	0.031**
	(101.8)	(59.1)	(0.047)	(0.032)	(0.039)	(0.014)	(0.053)	(0.038)	(0.038)	(0.015)
Dependent variable mean over 2006-08	*101.2*	*60.3*	*0.065*	*0.063*	*0.032*	*0.029*	*0.075*	*0.077*	*0.027*	*0.025*
Discontinuity estimate to baseline mean ratio	*1.99*	*1.36*	*1.20*	*1.02*	*1.91*	*0.80*	*1.21*	*0.91*	*2.24*	*1.24*
Difference	119.3		0.013		0.039		0.021		0.029	
	(117.7)		(0.057)		(0.041)		(0.066)		(0.041)	
Firms	1,969	3,919	1,969	3,919	1,969	3,919	1,969	3,919	1,969	3,919

Note: OLS estimates are based on the RD Design in equations (1) and (2). The running variable is total assets in 2007 with a threshold of €86m. Baseline sample includes firms with total assets in 2007 within €25m of the threshold (i.e., between €61m and €111m). Controls include first order polynomials of running variable separately for each side of the threshold. Robust standard errors are in brackets.

Panel A: Biotechnology and pharmaceutical (BTP) patents are those classified into either patent field (11) Analysis of biological materials, (15) Biotechnology, or (16) Pharmaceuticals. BTP-intensive industries (columns 1, 3, 5, 7, and 9) are top 20 three-digit SIC industries in total number of BTP patent applications over 2006-11.

Panel B: Information and communication technology (ICT) patents are those classified into either patent field (4) Digital communication, (6) Computer technology, or (7) IT methods for management. ICT-intensive industries (columns 1, 3, 5, 7, and 9) are top 20 three-digit SIC industries in total number of ICT patent applications over 2006-11.

*** denotes statistical significance at the 1% level, ** 5% level, * 10% level.

Table A9. Effects on the probabilities of doing any R&D or filing any patents

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Dependent variable	**Indicator: R&D exp. > 0**			**Indicator: All patent family count > 0**				
Year	2009	2010	2011	2009	2010	2011	2012	2013
Below-assets-threshold indicator (in 2007)	0.008	0.006	0.013	0.011*	0.008	0.014*	0.013**	0.018***
	(0.011)	(0.012)	(0.011)	(0.007)	(0.007)	(0.007)	(0.006)	(0.007)
Dependent variable mean	*0.036*	*0.041*	*0.045*	*0.017*	*0.017*	*0.017*	*0.015*	*0.016*
Firms	5,888	5,888	5,888	5,888	5,888	5,888	5,888	5,888

Note: OLS estimates are based on the RD Design in equations (1) and (2). The running variable is total assets in 2007 with a threshold of €86m. Baseline sample includes firms with total assets in 2007 within €25m of the threshold (i.e., between €61m and €111m). Controls include first order polynomials of running variable separately for each side of the threshold. Robust standard errors are in brackets. Dependent variables are indicators of whether a firm has R&D expenditure or files patents during the corresponding year.

*** denotes statistical significance at the 1% level, ** 5% level, * 10% level.

Table A10. Heterogeneous effects of R&D tax relief by past R&D and patents

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
Dependent variable	**R&D expenditure (£ *'000*), 2009-11 avg.**		**All patent family count, 2009-13 avg.**		**EPO patent count, 2009-13 avg.**		**UK patent count, 2009-13 avg.**		**US patent count, 2009-13 avg.**	
Subsample	Past > 0	Past = 0	Past > 0	Past = 0	Past > 0	Past = 0	Past > 0	Past = 0	Past > 0	Past = 0
Below-assets-threshold in 2007	1,708*	6.3	1.50**	0.002	1.40**	-0.000	1.80**	0.007	1.89***	-0.002
	(885)	(9.6)	(0.68)	(0.005)	(0.63)	(0.002)	(0.91)	(0.005)	(0.66)	(0.002)
Dependent variable mean over 2006-08	*1,682*	*0.0*	*2.18*	*0.00*	*1.51*	*0.00*	*2.96*	*0.00*	*1.42*	*0.00*
Difference	1,702*		1.50**		1.40**		1.79**		1.89***	
	(879)		(0.67)		(0.62)		(0.90)		(0.65)	
Firms	259	5,629	172	5,716	117	5,771	152	5,736	106	5,782

Note: OLS estimates are based on the RD Design in equations (1) and (2). The running variable is total assets in 2007 with a threshold of €86m. Baseline sample includes firms with total assets in 2007 within €25m of the threshold (i.e., between €61m and €111m). Controls include first order polynomials of running variable separately for each side of the threshold. Robust standard errors are in brackets. Past period is the pre-policy period of 2006-08.

*** denotes statistical significance at the 1% level, ** 5% level, * 10% level.

Table A11. Heterogeneous effects of R&D tax relief by industry patenting intensity

Panel A. OLS regressions

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
Dependent variable	**R&D expenditure (£ '000), 2009-11 avg.**		**All patent family count, 2009-13 avg.**		**EPO patent count, 2009-13 avg.**		**UK patent count, 2009-13 avg.**		**US patent count, 2009-13 avg.**	
Subsample	High patent	Low patent	High patent	Low patent	High patent	Low patent	High patent	Low patent	High patent	Low patent
Below-assets-threshold in 2007	167.4*	107.8	0.160**	0.017	0.078**	0.014	0.184**	0.017	0.084**	0.009
	(95.2)	(68.3)	(0.065)	(0.011)	(0.039)	(0.012)	(0.073)	(0.014)	(0.038)	(0.007)
Dependent variable mean over 2006-08	*124.7*	*25.0*	*0.118*	*0.020*	*0.058*	*0.007*	*0.140*	*0.024*	*0.047*	*0.006*
Difference	59.5		0.142**		0.064		0.167**		0.075*	
	(117.2)		(0.066)		(0.041)		(0.074)		(0.039)	
Firms	2,272	2,232	2,272	2,232	2,272	2,232	2,272	2,232	2,272	2,232

Panel B. Patent IV regressions

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Dependent variable (2009-13 average)	**All patent family count**		**EPO patent count**		**UK patent count**		**US patent count**	
Subsample	High patent	Low patent	High patent	Low patent	High patent	Low patent	High patent	Low patent
R&D expenditure *(£m)*, 2009-11 average	0.954	0.161	0.463	0.128	1.101	0.162	0.500	0.080
	(0.607)	(0.103)	(0.312)	(0.081)	(0.687)	(0.158)	(0.325)	(0.051)
Firms	2,272	2,232	2,272	2,232	2,272	2,232	2,272	2,232

Note: Baseline sample includes firms with total assets in 2007 within €25m of the threshold (i.e., between €61m and €111m). Robust standard errors are in brackets. Industry patenting intensity is calculated as the share of firms in the four-digit SIC industry having filed any patent before 2007. High (low) patenting subsample includes firms in industries above (below) median in patenting intensity. Examples of high-patenting industries include electric domestic appliances, basic pharmaceutical products, medical and surgical equipment, organic and inorganic basic chemicals, optical and photographic equipment, etc.

Panel A: OLS estimates are based on the RD Design in equations (1) and (2). The running variable is total assets in 2007 with a threshold of €86m. Controls include first order polynomials of running variable separately for each side of the threshold.

Panel B: IV estimates are based on equation (3). Instrumental variable is the indicator whether total assets in 2007 is below €86m. Controls include first order polynomial of RDD running variable (total assets in 2007) separately for each side of the threshold.

*** denotes statistical significance at the 1% level, ** 5% level, * 10% level.

Table A12. Heterogeneous effects of R&D tax relief by firm's past capital investments

Panel A. OLS regressions

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
Dependent variable	**R&D expenditure (£ *'000*), 2009-11 avg.**		**All patent family count, 2009-13 avg.**		**EPO patent count, 2009-13 avg.**		**UK patent count, 2009-13 avg.**		**US patent count, 2009-13 avg.**	
Subsample	Past inv. > 0	Past inv. = 0	Past inv. > 0	Past inv. = 0	Past inv. > 0	Past inv. = 0	Past inv. > 0	Past inv. = 0	Past inv. > 0	Past inv. = 0
Below-assets-threshold in 2007	305.5***	-36. 7	0.148***	-0.000	0.079**	-0.002	0.166**	-0.000	0.088**	-0.000
	(106.4)	(30.0)	(0.055)	(0.013)	(0.034)	(0.007)	(0.065)	(0.015)	(0.034)	(0.007)
Dependent variable mean over 2006-08	*159.6*	*4.4*	*0.123*	*0.016*	*0.058*	*0.007*	*0.147*	*0.019*	*0.048*	*0.007*
Difference	342.2***		0.148***		0.080**		0.166**		0.088**	
	(110.6)		(0.056)		(0.035)		(0.067)		(0.035)	
Firms	2,640	3,248	2,640	3,248	2,640	3,248	2,640	3,248	2,640	3,248

Panel B. Patent IV regressions

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Dependent variable (2009-13 average)	**All patent family count**		**EPO patent count**		**UK patent count**		**US patent count**	
Subsample	Past inv. > 0	Past inv. = 0	Past inv. > 0	Past inv. = 0	Past inv. > 0	Past inv. = 0	Past inv. > 0	Past inv. = 0
R&D expenditure *(£m)*, 2009-11 average	0.483**	0.004	0.257**	0.043	0.542**	0.002	0.288**	0.001
	(0.217)	(0.351)	(0.121)	(0.195)	(0.256)	(0.394)	(0.130)	(0.189)
Firms	2,640	3,248	2,640	3,248	2,640	3,248	2,640	3,248

Note: Baseline sample includes firms with total assets in 2007 within €25m of the threshold (i.e., between €61m and €111m). Robust standard errors are in brackets. Past capital investments is calculated as average machinery and plant investments over 2005-07 reported in CT600 (as coverage of capital expenditure in FAME is limited).

Panel A: OLS estimates are based on the RD Design in equations (1) and (2). The running variable is total assets in 2007 with a threshold of €86m. Controls include first order polynomials of running variable separately for each side of the threshold.

Panel B: IV estimates are based on equation (3). Instrumental variable is the indicator whether total assets in 2007 is below €86m. Controls include first order polynomial of RDD running variable (total assets in 2007) separately for each side of the threshold.

*** denotes statistical significance at the 1% level, ** 5% level, * 10% level.

Table A13. Heterogeneous effects of R&D tax relief by industry external finance dependence

	(1)	(2)	(3)	(4)	(5)	(6)
Dependent variable	**R&D expenditure *(£ '000)* 2009-11 average**			**All patent family count 2009-13 average**		
	Full	High external finance dependence	Low external finance dependence	Full	High external finance dependence	Low external finance dependence
Below-assets-threshold indicator (in 2007)	171.4**	203.6*	70.3	0.100**	0.136**	0.033*
	(72.6)	(105.3)	(55.8)	(0.041)	(0.063)	(0.018)
Below-assets-threshold indicator # RZ index	8.2			0.004		
	(6.2)			(0.003)		
Difference		113.3 (119.1)			0.103 (0.066)	
Dependent variable mean over 2006-08	*75.2*	*111.6*	*40.0*	*0.069*	*0.095*	*0.045*
Discontinuity estimate to baseline mean ratio		*1.82*	*1.76*		*1.43*	*0.73*
Firms	4,503	2,217	2,286	4,503	2,217	2,286

Note: OLS estimates are based on the RD Design in equations (1) and (2). The running variable is total assets in 2007 with a threshold of €86m. Baseline sample includes firms with total assets in 2007 within €25m of the threshold (i.e., between €61m and €111m). Controls include first order polynomials of the running variable separately for each side of the threshold Robust standard errors are in brackets. Rajan-Zingales (1998) index for industry external finance dependence (i.e., industry-level across-firm average of $\frac{capex-cashflow}{capex}$) is calculated at three-digit SIC industry level using UK firm data over 2000-05 (Rajan and Zingales, 1998). Firms in industries with high Rajan-Zingales index are more likely to be financially constrained. High (low) external finance dependence subsample includes firms with above (below) median industry Rajan-Zingales index. All right-hand-side variables are fully interacted with industry Rajan-Zingales index in columns (1) and (4).

*** denotes statistical significance at the 1% level, ** 5% level, * 10% level.

Table A14: Effects of R&D tax relief on non-qualifying expense categories

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
Sample	Full baseline sample					R&D performing firms				
Dependent variable (2009-11 average, *£ ’000*)	**Admin exp.**	**Admin exp., excl. R&D**	**Total exp., excl. R&D**	**Capex imputed from PPE**	**Qual. M&P exp.**	**Admin exp.**	**Admin exp., excl. R&D**	**Total exp., excl. R&D**	**Capex imputed from PPE**	**Qual. M&P exp.**
Below-assets-threshold in 2007	480	287	-1,301	20	32	1,553	-344	-5,254	-311	254
	(1,179)	(1,171)	(3,558)	(230)	(40)	(4,197)	(4,138)	(11,947)	(510)	(226)
Dependent variable mean over 2006-08	*14,806*	*14,715*	*42,875*	*3,464*	*505*	*23,490*	*22,340*	*71,470*	*2,459*	*1,743*
Firms	4,441	4,441	4,569	3,061	5,575	323	323	326	318	329

Notes: OLS estimates are based on the RD Design analogous to equations (1) and (2). The running variable is total assets in 2007 with a threshold of €86m. Controls include first order polynomials of the running variable separately for each side of the threshold. Robust standard errors are in brackets. Columns (1)-(5) employ the full baseline sample for firms with total assets in 2007 within €25m of the threshold (i.e., between €61m and €111m). Columns (6)-(10) use the subsample of R&D performing firms during 2009-11 that are in the baseline sample. The dependent variables are average over the post-policy years for which data are not missing. Columns (1) and (6) look at total administrative expenses reported in FAME. Columns (2) and (7) look at total administrative expenses minuses qualifying R&D expenditure. Columns (3) and (8) look at total expenses reported in FAME minuses qualifying R&D expenditure. Column (4) and (9) look at capital expenditure imputed from net change in balance sheet’s property, plant, and equipment reported in FAME. Column (5) and (10) look at qualifying machinery and plant investments reported in CT600 (for capital allowance tax relief purpose).

*** denotes statistical significance at the 1% level, ** 5% level, * 10% level.

Table A15. Effects of R&D tax relief on other measures of firm performance

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)
	Before (pre-policy)			After (post-policy)					Before	5yr After	5yr Diff.
Year	2006	2007	2008	2009	2010	2011	2012	2013	2006-08 average	2009-11 average	5yr After - Before
Panel A. Dependent variable: Ln(Sales)											
Below-assets-threshold indicator (in 2007)	-0.187	0.029	-0.102	0.212	0.404**	0.307	0.198	0.188	-0.023	0.170	0.193
	(0.170)	(0.167)	(0.162)	(0.180)	(0.187)	(0.192)	(0.204)	(0.217)	(0.157)	(0.181)	(0.123)
Firms	3,292	3,439	3,394	3,312	3,296	3,260	3,207	3,153	3,451	3,451	3,451
Panel B. Dependent variable: Ln(Employment)											
Below-assets-threshold indicator (in 2007)	-0.012	0.102	0.079	0.104	0.258*	0.283*	0.289*	0.364**	0.0215	0.240*	0.219**
	(0.126)	(0.123)	(0.131)	(0.140)	(0.148)	(0.153)	(0.156)	(0.160)	(0.125)	(0.143)	(0.095)
Firms	2,468	2,548	2,430	2,443	2,553	2,470	2,370	2,281	2,403	2,403	2,403
Panel C. Dependent variable: Ln(Capital)											
Below-assets-threshold indicator (in 2007)	-0.013	-0.032	-0.007	-0.016	-0.004	0.015	0.070	0.125	-0.065	0.010	0.075
	(0.120)	(0.109)	(0.113)	(0.122)	(0.131)	(0.135)	(0.142)	(0.146)	(0.108)	(0.125)	(0.084)
Firms	3,724	3,959	3,793	3,609	3,457	3,322	3,205	3,074	3,665	3,665	3,665
Panel D. Dependent variable: Total factor productivity											
Below-assets-threshold indicator (in 2007)	-0.069	0.037	0.020	0.178	0.265	0.127	0.146	0.184	0.070	0.210	0.140
	(0.171)	(0.162)	(0.152)	(0.166)	(0.173)	(0.178)	(0.191)	(0.201)	(0.157)	(0.163)	(0.113)
Firms	1,590	1,629	1,575	1,527	1,508	1,487	1,418	1,367	1,605	1,605	1,605

Note: OLS estimates are based on the RD Design analogous to equations (1) and (2). The running variable is total assets in 2007 with a threshold of €86m. Baseline sample includes firms with total assets in 2007 within €25m of the threshold (i.e., between €61m and €111m). Controls include first order polynomials of the running variable separately for each side of the threshold and two-digit SIC industry fixed effects. (All results are qualitatively similar without these fixed effects.) Robust standard errors are in brackets. **Panel A** uses sales from CT600. **Panel B** uses employment (from FAME). **Panel C** uses fixed assets (from FAME). **Panel D** uses total factor productivity from Olley-Pakes production function estimation at two-digit SIC industry level (see Appendix B.5 for details). Columns (9)-(10) condition on the "balanced" sample where we observe the outcome variable in at least one year of the pre-policy sample and one year of the post-policy sample (i.e., it is a subsample of the observations in columns 1-8).

*** denotes statistical significance at the 1% level, ** 5% level, * 10% level.

Table A16. Estimating impacts of R&D tax relief using other SME criteria

Panel A.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
SME criterion	Total assets		Sales				Employment	
Dependent variable	**R&D exp. *(£ '000)*, 09-11 avg.**	**All patent count, 09-13 avg.**	**R&D exp. *(£ '000)*, 09-11 avg.**	**All patent count, 09-13 avg.**	**R&D exp. *(£ '000)*, 09-11 avg.**	**All patent count, 09-13 avg.**	**R&D exp. *(£ '000)*, 09-11 avg.**	**All patent count, 09-13 avg.**
Below-SME-threshold indicator (in 2007)	123.3**	0.069***	138.6**	0.027	152.1	0.083	86.4	0.138**
	(52.1)	(0.026)	(64.2)	(0.044)	(123.2)	(0.065)	(104.6)	(0.056)
Dependent variable mean over 2006-08	*74.0*	*0.064*	*119.5*	*0.087*	*194.3*	*0.122*	*209.4*	*0.148*
Discontinuity estimate to baseline mean ratio	*1.67*	*1.09*	*1.16*	*0.31*	*0.78*	*0.68*	*0.41*	*0.93*
Sample	Total assets in [€61m, €111m]		Sales in [€50m, €150m]		Sales in [€50m, €150m] & total assets > €86m		Employment in [300, 700]	
Firms	5,888	5,888	7,101	7,101	2,085	2,085	4,526	4,526

Panel B.

	(1)	(2)	(3)	(4)	(5)	(6)
Specification	First stage	Reduced form	IV	First stage	Reduced form	IV
Dependent variable	**R&D exp. *(£ '000)*, 09-11 avg.**	**All patent count, 09-13 avg.**	**All patent count, 09-13 avg.**	**R&D exp. *(£ '000)*, 09-11 avg.**	**All patent count, 09-13 avg.**	**All patent count, 09-13 avg.**
Bellow-assets-threshold indicator (in 2007)	107.9*	0.129***		68.2*	0.072***	
	(57.6)	(0.045)		(37.3)	(0.026)	
Below-sales-threshold indicator (in 2007)	131.4**	0.024		71.6*	-0.013	
	(63.8)	(0.044)		(40.0)	(0.023)	
R&D expenditure (*£m*), 2009-11 average			0.696**			0.366
			(0.334)			(0.307)
Dependent variable mean over 2006-08	*119.5*	*0.087*	*0.087*	*105.0*	*0.080*	0.080
Joint F-statistics (p-value)	3.26 (0.04)	4.73 (0.01)		2.30 (0.10)	5.70 (0.00)	
Sample	Sales in [€50m, €150m]			Total assets in [€61m, €111m] or sales in [€50m, €150m]		
Firms	7,091	7,091	7,091	9,751	9,751	9,751

Note: OLS estimates are based on the RD Design analogous to equations (1) and (2). Controls include first order polynomials of running variable separately for each side of the threshold. Robust standard errors are in brackets.

Panel A: The running variable in columns (1) and (2) is total assets in 2007 with threshold of €86m; columns (3) and (6) sales in 2007 with threshold of €100m; columns (7) and (8) employment in 2007 with threshold of 499.

Panel B: The running variables are (i) total assets in 2007 with threshold of €86m and (ii) sales in 2007 with threshold of €100m. Columns (3) and (6) estimate the RD-based IV model analogous to equation (3) in which the instrumental variables are (i) the indicator of whether total assets in 2007 is below €86m and (ii) the indicator of whether sales in 2007 is below €100m. Reported joint F-statistics for are for below-assets-threshold indicator and below-sales-threshold indicator. P-values of Anderson-Rubin weak-instrument-robust inference tests in columns (3) and (6) are 0.009 and 0.003 respectively.

*** denotes statistical significance at the 1% level, ** 5% level, * 10% level.

Table A17. R&D technology spillovers on R&D and patents

	(1)	(2)	(3)	(4)	(5)	(6)
Specification	First stage, OLS		Reduced form, OLS	IV		
Dependent variable	**$spilltechRD$ (£ *million*) 2009-11 avg.**	**R&D exp. (£ *million*), 2009-11 avg.**	**All patent fam. count, 2009-13 avg.**	**R&D exp., (£ *million*), 2009-11 avg.**	**All patent fam. count, 2009-13 avg.**	**All patent fam. count, 2009-13 avg.**
$spilltechE$ *(sum tech. proximity x indicator)*	11.18***	0.053	0.174**			
	(2.20)	(0.089)	(0.074)			
Below-assets-threshold indicator (in 2007)	0.40	0.156***	0.070**	0.154**	0.063*	
	(1.28)	(0.060)	(0.029)	(0.060)	(0.037)	
$spilltechR$ *(sum tech. proximity x £m)*				0.005	0.016*	0.014
				(0.008)	(0.008)	(0.011)
R&D expenditure (*£m)*, 2009-11 average						0.412
						(1.959)
Dependent variable mean over 2006-08	*25.02*	*0.070*	*0.061*	*0.070*	*0.061*	*0.061*
Firms	8,818	8,818	8,818	8,818	8,818	8,818

Note: Sample of firms with total assets in 2007 between €51m and €121m. Standard errors in brackets are corrected using 1,000 bootstrap replications over firms. Controls include second order polynomials of total assets in 2007, separately for each side of the assets threshold of €86m; $F_j(Z_{2007}) = \sum_{i,i\neq j} \omega_{ij} f(z_{i,2007})$ where $f(z_{i,2007})$'s are second order polynomials of spillover-generating firm i's total assets in 2007, also separately for each side of the assets threshold (see Appendix C.2); and $techconnect_j = \sum_{i,i\neq j} \omega_{ij}$ – a measure for spillover-generating firm j's level of connectivity in technology space. In column (5), adjusted first-stage F-statistic is 26.9; and the p-value of Anderson-Rubin weak-instrument-robust inference test is 0.018, indicating that the IV estimates are statistically different from zero even in the possible case of weak IV. In column (6), the instrument variable for $spilltechR$ is $spilltechE$ and instrument variable for R&D expenditure is below-assets-threshold indicator.

*** denotes statistical significance at the 1% level, ** 5% level, * 10% level.

Table A18. Tax-price elasticities of R&D and patents using different approaches

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
	SME status	**R&D expenditure (£ '000)**				**All patent family count**				**R&D user cost**	**Elasticity**	
Approach	Fuzziness estimate	Discon-tinuity estimate	Adjusted discon-tinuity estimate	Pre-policy baseline mean	R&D difference	Discon-tinuity estimate	Adjusted discon-tinuity estimate	Pre-policy baseline mean	Patent difference	Tax-adjusted user cost difference	R&D (wrt. R&D cost)	Patent (wrt. R&D cost)
(1) Baseline	**0.353**	**60.4**	**171.2**	**74.0**	**1.073**	**0.042**	**0.119**	**0.064**	**0.964**	**0.269**	**3.989**	**3.583**
(2) Log difference elasticity	0.353	60.4	171.2	74.0	**1.198**	0.042	0.119	0.064	**1.051**	**0.271**	4.422	3.878
(3) SME status over 2009-11	**0.248**	60.4	243.7	74.0	1.245	0.042	0.169	0.064	1.139	0.269	4.626	4.236
(4) SME status over 2008-09	**0.464**	60.4	130.3	74.0	0.936	0.042	0.090	0.064	0.829	0.269	3.481	3.081
(5) LDV discontinuity estimate	0.353	**63.4**	179.5	74.0	1.096	**0.049**	0.140	0.064	1.046	0.269	4.076	3.889
(6) Pre-policy mean over 2006-07	0.353	60.4	171.2	**77.6**	1.049	0.042	0.119	**0.065**	0.953	0.269	3.899	3.544
(7) R&D performing firms	0.353	**672**	1902	**1,148**	0.906	**0.304**	0.861	**0.680**	0.775	0.269	3.369	2.881
(8) 2007 assets in [€51m, €121m]	**0.345**	**51.8**	150.2	**69.8**	1.037	**0.038**	0.109	**0.058**	0.968	0.269	3.855	3.599
(9) Financially unconstrained firms	**0.965**	**9.7**	10.1	**24.2**	0.346	**0.029**	0.030	**0.025**	0.754	0.269	1.285	2.801
(10) Small profits corporate tax rate	0.353	60.4	171.2	74.0	1.073	0.042	0.119	0.064	0.964	**0.228**	4.706	4.227

Note: Baseline approach (i.e., arc elasticity) in **row (1)** is explained in detail in subsection 7.2 and the note to Panel A of Table A19. Log-difference-elasticity approach in **row (2)** is explained in detail in the note to Panel B of Table A19. Rows (3)-(8) employ the baseline arc-elasticity approach as in row (1) and different alternative input estimates. **Rows (3) and (4)** use alternative estimates for how "sharp" the below-assets-threshold indicator is as an instrument for SME status, based on SME status over 2009-11 (row 3) and SME status over 2008-09 (row 4). These estimates are reported in columns (6) and (4) of Table 9 respectively. **Row (5)** uses the discontinuity estimates with lagged dependent variable control from column (10) of Table 3 (for R&D) and column (17) of Table 4 (for patents). **Row (6)** uses average R&D and patents over 2006-07 as the pre-policy baseline means. **Row (7)** uses estimates from subsample of R&D performing firms (Table 9, column 5's sample). **Row (8)** uses larger baseline sample of firms with 2007 total assets between €51m and €121m and triangular kernel weights. Relevant estimates are reported in Tables A4 and A5. **Row (9)** reports elasticity estimates in subsample of financial unconstrained firms (Table 7, column 3's sample), using input estimates from this subsample. **Row (10)** applies the small profits corporate tax rate in calculations of tax-adjusted user costs (see Appendix E.4 for details). Differences between each approach and the baseline case in row (1) are highlighted in bold (for input estimates only).

Table A19. Bootstrapping elasticity estimates

Panel A. Arc elasticity

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)
	SME status	**R&D expenditure (£ *'000*)**				**All patent family count**				**Elasticity**	
	First-stage estimate	3yr After - Before estimate	Adjusted 3yr After - Before estimate	Pre-policy baseline mean	Arc % R&D difference	5yr After - Before estimate	Adjusted 5yr After - Before estimate	Pre-policy baseline mean	Arc % patent difference	R&D (wrt. R&D user cost)	Patent (wrt. R&D user cost)
Baseline sample estimates	0.353	60.4	171.2	74.0	1.073	0.042	0.119	0.064	0.964	**3.989**	**3.583**
Bootstrapped distribution											
5th percentile	0.206	8.1	24.6	58.4	0.292	0.008	0.019	0.049	0.301	**1.085**	**1.119**
10th percentile	0.236	19.8	50.9	61.5	0.529	0.016	0.042	0.052	0.502	1.966	1.866
25th percentile	0.293	39.3	108.4	67.4	0.837	0.027	0.074	0.057	0.738	3.113	2.743
50th percentile	0.357	60.4	169.3	73.8	1.079	0.042	0.118	0.064	0.963	4.010	3.580
75th percentile	0.414	82.2	247.1	80.1	1.248	0.056	0.170	0.070	1.145	4.640	4.258
90th percentile	0.468	103.7	337.1	86.1	1.380	0.072	0.232	0.076	1.292	5.130	4.801
95th percentile	0.501	119.1	404.3	90.6	1.462	0.081	0.282	0.079	1.385	5.436	5.148

Note: Panel A reports baseline estimators used to calculate "arc-percentage-difference" R&D and patent elasticities, together with their empirical distributions (see subsection 7.2 for details). The estimators' empirical distributions are derived from 1,000 bootstrap replications. In each replication, we draw with replacement 361 observations from the subsample of 361 post-policy R&D performing firms, and 5,527 (= 5,888-361) observations from the remaining subsample of 5,527 firms. **Column (1)** reports the discontinuity estimate in column (5) of Table 9 and its empirical distribution. **Column (2)** corresponds to column (9) of Table 3, **column (4)** R&D pre-policy baseline mean, **column (6)** column (16) of Table 4, and **column (8)** patent pre-policy baseline mean. **Column (3)** reports policy-induced R&D, estimated as $\frac{col.(2)}{col.(1)}$. **Column (5)** reports policy-induced percentage difference in R&D, $\frac{R_{SME}-R_{LCO}}{(R_{SME}+R_{LCO})/2}$, estimated as $\frac{col.(3)}{col.(3)/2+col.(4)}$. **Column (7)** reports policy-induced patents, estimated as $\frac{col.(5)}{col.(1)}$. **Column (9)** reports policy-induced percentage difference in patent, $\frac{PAT_{SME}-PAT_{LCO}}{(PAT_{SME}+PAT_{LCO})/2}$, estimated as $\frac{col.(7)}{col.(7)/2+col.(8)}$. **Column (10)** reports R&D elasticity with respect to its tax-adjusted user cost, $\frac{\%\text{ difference in }R}{\%\text{ difference in }\rho}$, estimated as $\frac{col.(5)}{0.269}$ (percentage difference in user cost is 0.269, see column 7 of Table A2). **Column (11)** reports patent elasticity with respected to R&D tax-adjusted user cost, $\frac{\%\text{ difference in }PAT}{\%\text{ difference in }\rho}$, estimated as $\frac{col.(9)}{0.269}$.

Panel B. "Log-difference" elasticity

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)
	SME status	**R&D expenditure**				**All patent family count**				**Elasticity**	
	First-stage estimate	3yr After - Before estimate	Adjusted 3yr After - Before estimate	Pre-policy baseline mean	Log R&D difference	5yr After - Before estimate	Adjusted 5yr After - Before estimate	Pre-policy baseline mean	Log patent difference	R&D (wrt. R&D user cost)	Patent (wrt. R&D user cost)
Baseline sample estimates	0.353	60.4	171.2	74.0	1.198	0.042	0.119	0.064	1.051	**4.422**	**3.878**
Bootstrapped distribution											
5th percentile	0.206	8.1	24.6	58.4	0.302	0.008	0.019	0.049	0.303	**1.113**	**1.119**
10th percentile	0.236	19.8	50.9	61.5	0.544	0.016	0.042	0.052	0.513	2.006	1.893
25th percentile	0.293	39.3	108.4	67.4	0.893	0.027	0.074	0.057	0.774	3.296	2.857
50th percentile	0.357	60.4	169.3	73.8	1.207	0.042	0.118	0.064	1.050	4.454	3.874
75th percentile	0.414	82.2	247.1	80.1	1.464	0.056	0.170	0.070	1.303	5.404	4.808
90th percentile	0.468	103.7	337.1	86.1	1.696	0.072	0.232	0.076	1.536	6.260	5.668
95th percentile	0.501	119.1	404.3	90.6	1.864	0.081	0.282	0.079	1.705	6.876	6.293

Note: Panel B reports baseline estimators used to calculate "log-difference" R&D and patent elasticities, together with their empirical distributions. The estimators' empirical distributions are derived from 1,000 bootstrap replications. In each replication, we draw with replacement 361 observations from the subsample of 361 post-policy R&D performing firms, and 5,527 (= 5,888-361) observations from the remaining subsample of 5,527 firms. **Column (1)** reports the discontinuity estimate in column (5) of Table 9 and its empirical distribution. **Column (2)** corresponds to column (9) of Table 3, **column (4)** R&D pre-policy baseline mean, **column (6)** column (16) of Table 4, and **column (8)** patent pre-policy baseline mean. **Column (3)** reports policy-induced R&D, estimated as $\frac{col.(2)}{col.(1)}$. **Column (5)** reports policy-induced log difference in R&D, $\ln\frac{R_{SME}}{R_{LCO}}$, estimated as $\ln\frac{col.(3)+col.(4)}{col.(4)}$. **Column (7)** reports policy-induced patents, estimated as $\frac{col.(5)}{col.(1)}$. **Column (9)** reports policy-induced log difference in patent, $\ln\frac{PAT_{SME}}{PAT_{LCO}}$, estimated as $\ln\frac{col.(7)+col.(8)}{col.(8)}$. **Column (10)** reports R&D elasticity with respect to its tax-adjusted user cost, $\frac{\ln(R_{SME}/R_{LCO})}{\ln(\rho_{SME}/\rho_{LCO})}$, estimated as $\frac{col.(5)}{0.271}$ (log difference in user cost is 0.271, see column 8 of Table A2). **Column (11)** reports patent elasticity with respected to R&D tax-adjusted user cost, $\frac{\ln(PAT_{SME}/PAT_{LCO})}{\ln(\rho_{SME}/\rho_{LCO})}$, estimated as $\frac{col.(9)}{0.271}$.

Table A20. Value for money analysis of R&D Tax Relief Scheme

Year	2006	2007	2008	2009	2010	2011	2006-11 average
Panel A. Policy parameters							
SME enhancement rate e_{SME}	50%	50%	67%	75%	75%	100%	
SME payable credit rate c_{SME}	16%	16%	15%	14%	14%	12.5%	
SME effective corporate tax rate τ_{SME}	19%	19%	21%	21%	21%	20%	
LCO enhancement rate e_{LCO}	25%	25%	30%	30%	30%	30%	
LCO effective corporate tax rate τ_{LCO}	30%	30%	28%	28%	28%	26%	
Panel B. SME tax deduction case							
Tax-adjusted user cost of R&D ρ	0.177	0.177	0.165	0.160	0.160	0.150	
Value for money ratio μ	4.19	4.19	3.99	3.89	3.89	3.63	3.87
Exchequer costs Δ_{EC} *(£m)*	50	60	80	130	160	210	115
Additional R&D Δ_R *(£m)*	210	251	319	506	622	762	445
Panel C. SME payable tax credit case							
Tax-adjusted user cost of R&D ρ	0.152	0.152	0.151	0.151	0.151	0.150	
Value for money ratio μ	2.94	2.94	2.92	2.92	2.92	2.90	2.92
Exchequer costs Δ_{EC} *(£m)*	150	180	190	190	190	220	187
Additional R&D Δ_R *(£m)*	440	528	555	555	555	639	545
Panel D. Large company deduction case							
Tax-adjusted user cost of R&D ρ	0.179	0.179	0.177	0.177	0.177	0.179	
Value for money ratio μ	1.54	1.54	1.50	1.50	1.50	1.46	1.50
Exchequer costs Δ_{EC} *(£m)*	480	550	730	670	750	780	660
Additional R&D Δ_R *(£m)*	741	849	1,095	1,005	1,125	1,139	992
Panel E: Aggregates							
Total Exchequer costs Δ_{EC} *(£m)*	680	790	1,000	990	1,100	1,210	962
Total additional R&D Δ_R *(£m)*	1,391	1,629	1,969	2,065	2,302	2,540	1,982
Value for money ratio $\mu = \Delta_R / \Delta_{EC}$	2.04	2.06	1.97	2.09	2.09	2.10	2.06
Total qualifying R&D *(£m)*	7,670	8,880	10,800	9,730	10,870	11,840	9,965
Fall of aggregate R&D without policy	18%	18%	18%	21%	21%	21%	20%

Note: Tax-adjusted user cost of R&D and value for money ratio are calculated using the formulae as described in Appendix F using the above policy parameters. In addition, real interest rate is 5% and depreciation rate is 15%. Tax-adjusted user cost of R&D without any tax relief is calculated to be 0.200. Tax-price elasticity of R&D among SMEs is -3.99 as estimated in subsection 7.2. Tax-price elasticity of R&D among large companies is -1.09 (i.e., the lower-bound elasticity estimate). Exchequer costs (Panels B-D) and total qualifying R&D (Panel E) come from HMRC national statistics. In Panels B-D, additional R&D is calculated as value for money ratios times Exchequer costs (i.e., $\Delta_R = \mu \times \Delta_{EC}$). In Panel E, total Exchequer costs and total additional R&D are the sums of the corresponding amounts in Panels B-D; value for money ratio is total Exchequer costs over total additional R&D; fall in aggregate R&D without policy if total additional R&D over total qualifying R&D.

Table B1. Descriptive statistics

Panel A. Full CT600 dataset

	Unit	**2006**	**2007**	**2008**	**2009**	**2010**	**2011**	**2006-2011**
No. firms	*Firm*	1,406,696	1,487,173	1,484,311	1,504,927	1,564,871	1,646,641	2,495,944
No. firms claiming R&D relief	*Firm*	6,431	7,429	8,334	9,144	10,150	12,003	20,730
SME Scheme								
No. firms claiming	*Firm*	5,153	5,855	6,570	7,354	8,238	9,921	20,205
Avg. qual. R&D expenditure	*£ (nom)*	257,752	268,904	266,730	244,854	263,811	258,541	1,569,728
Avg. est. Exchequer costs	*£ (nom)*	39,433	42,150	41,018	44,099	43,138	43,451	169,643
Large Company Scheme								
No. firms claiming	*Firm*	1,290	1,592	1,776	1,795	1,923	2,092	4,048
Avg. qual. R&D expenditure	*£ (nom)*	4,926,939	4,616,811	5,120,979	4,435,308	4,508,202	4,357,442	12,580,710
Avg. est. Exchequer costs	*£ (nom)*	371,097	346,616	412,088	376,405	382,284	357,870	1,030,878
SME subcontractors								
No. firms claiming	*Firm*	399	443	522	610	720	715	2,100
Avg. qual. R&D expenditure	*£ (nom)*	630,098	465,590	406,302	504,624	658,942	928,208	1,007,468
Avg. est. Exchequer costs	*£ (nom)*	47,406	48,014	43,043	42,618	46,771	56,809	315,560
Patenting								
No. firms having patents	*Firm*	3,093	3,085	2,965	2,806	2,682	2,662	9,420
Avg. number of patents	*Patent*	2.68	2.77	2.72	2.63	2.66	2.64	4.93
No. firms having EPO patents	*Firm*	1,453	1,448	1,376	1,409	1,358	1,125	4.770
Avg. number of EPO patents	*Patent*	0.95	0.90	0.82	0.83	0.47	0.17	4.95
No. firms having UK patents	*Firm*	3,262	3,316	3,228	3,083	2,989	2,965	8,986
Avg. number of UK patents	*Patent*	3.00	3.08	3.00	2.83	2.78	2.82	6.13

Panel B. Full FAME dataset

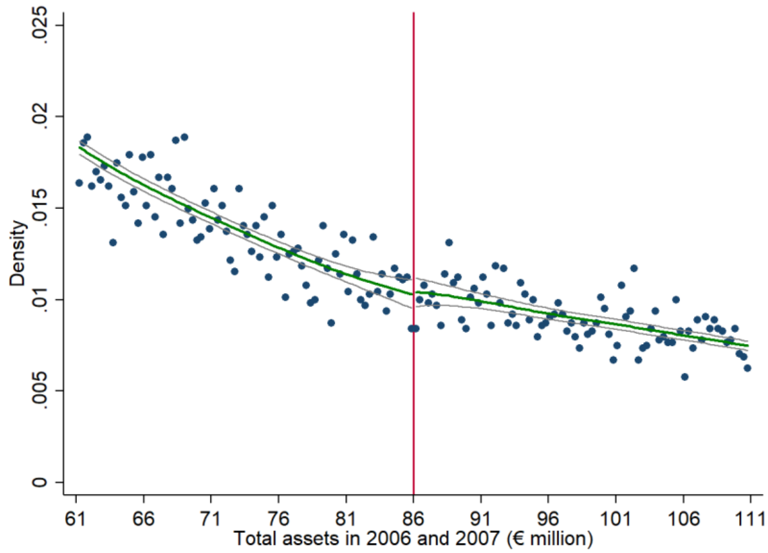
	Unit	**2006**	**2007**	**2008**	**2009**	**2010**	**2011**	**2006-2011**
No. firms	*Firm*	1,780,531	1,858,209	1,870,089	1,898,721	1,973,722	2,073,930	3,140,060
Variable coverage								
No. firms with total assets	*Firm*	1,732,169	1,807,743	1,818,448	1,843,896	1,914,848	2,015,058	3,012,397
Total assets coverage	*%*	97.3%	97.3%	97.2%	97.1%	97.0%	97.2%	95.9%
No. firms with sales	*Firm*	352,680	319,726	275,938	274,768	263,394	227,463	626,025
Sales coverage	*%*	19.8%	17.2%	14.8%	14.5%	13.3%	11.0%	19.9%
No. firms with employment	*Firm*	95,615	93,855	91,375	94,332	98,426	97,814	164,849
Employment coverage	*%*	5.4%	5.1%	4.9%	5.0%	5.0%	4.7%	5.2%

Panel C. CT600 and FAME matching

	Unit	**2006**	**2007**	**2008**	**2009**	**2010**	**2011**	**2006-2011**
No. CT600 firms that appear in FAME over 2006-11	*Firm*	1,353,844	1,427,132	1,442,619	1,468,000	1,529,317	1,598,012	2,358,948
As % CT600 firms	*%*	96.2%	96.0%	97.2%	97.5%	97.7%	97.0%	94.5%
Out of which								
No. firms claiming tax relief	*Firm*	6,411	7,409	8,298	9,105	10,108	11,937	20,627
As % CT600 R&D firms	*%*	99.7%	99.7%	99.6%	99.6%	99.6%	99.5%	99.5%
No. firms having patents	*Firm*	3,078	3,065	2,951	2,789	2,665	2,634	9,376
As % CT600 patenting firms	*%*	99.5%	99.4%	99.5%	99.4%	99.4%	98.9%	99.5%

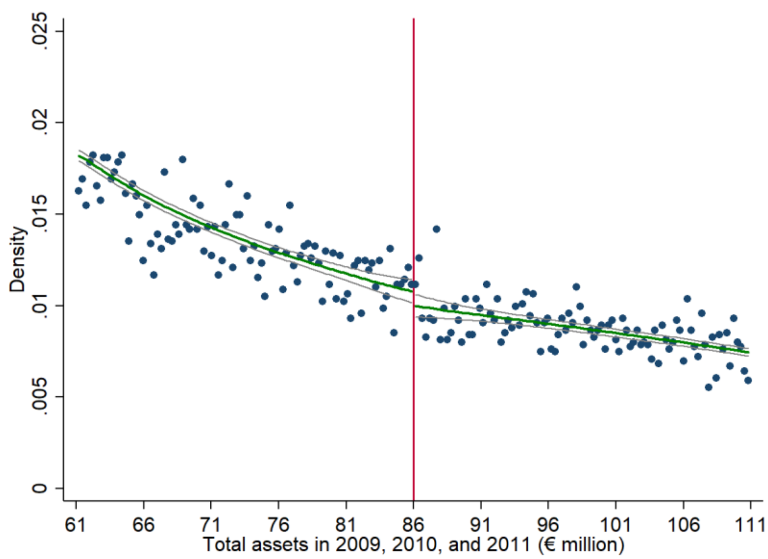
Note: Average qualifying R&D expenditure and estimated Exchequer costs are computed for firms with R&D tax relief claims in the corresponding year or period. Average patents, EPO patents, and UK patents are computed for firms with corresponding patent applications in corresponding year or period.

Figure A1. McCrary test for no manipulation at the SME assets threshold before the policy change



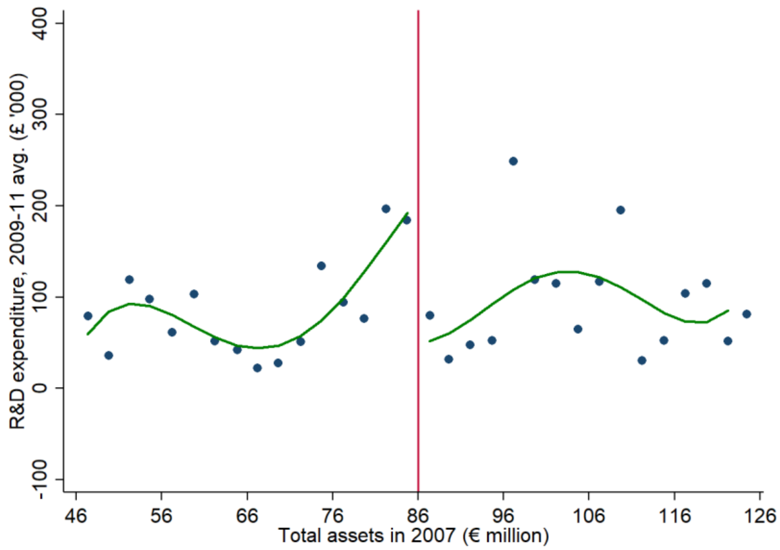
Note: This figure reports the McCrary test for discontinuity in distribution density of total assets at the 2008 new SME assets threshold of €86m before the policy change, pooling together total assets in 2006 and 2007. Estimation sample includes firms with total assets between €46m and €126m in each of the year. The discontinuity estimate (log difference in density height at the SME threshold) (standard error) is 0.013 (0.056).

Figure A2. McCrary test for no manipulation at the SME assets threshold after the policy change



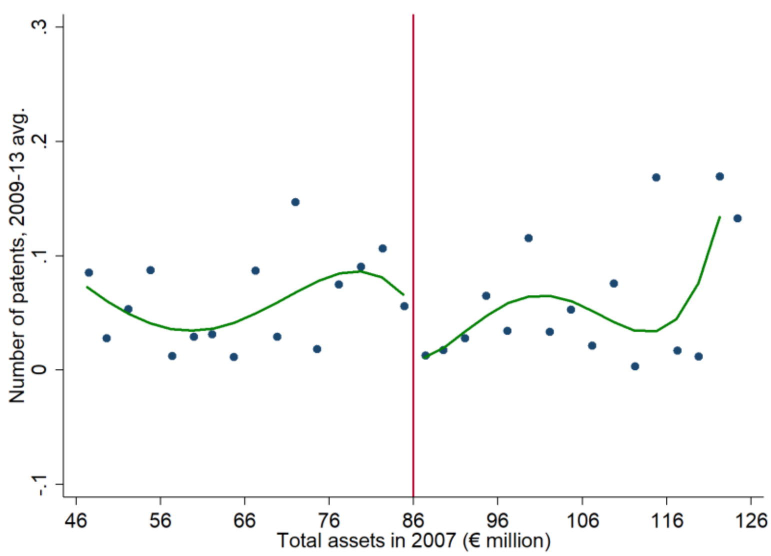
Note: This figure reports the McCrary test for discontinuity in distribution density of total assets at the 2008 new SME assets threshold of €86m after the policy change, pooling together total assets in 2009, 2010, and 2011. Estimation sample includes firms with total assets between €46m and €126m in each of the year. The discontinuity estimate (log difference in density height at the SME threshold) (standard error) is -0.072 (0.045).

<u>Figure A3. Discontinuity in average R&D expenditure over 2009-11 at the SME assets threshold</u>



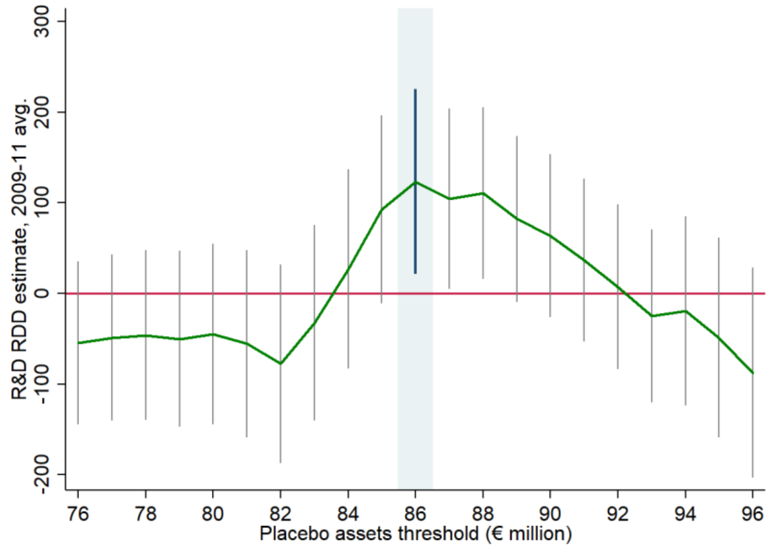
Note: This figure is produced by Calonico, Catteneo, and Titunik's (CCT) (2014) data-driven RD plot. The dependent variable is average R&D expenditure over 2009-11. The running variable is total assets in 2007 with a threshold of €86m. Controls include fourth order polynomials of the running variable separately on each side of the threshold. Bin size for the scatter plot is €2.5m.

<u>Figure A4. Discontinuity in average number of patents over 2009-13 at the SME assets threshold</u>



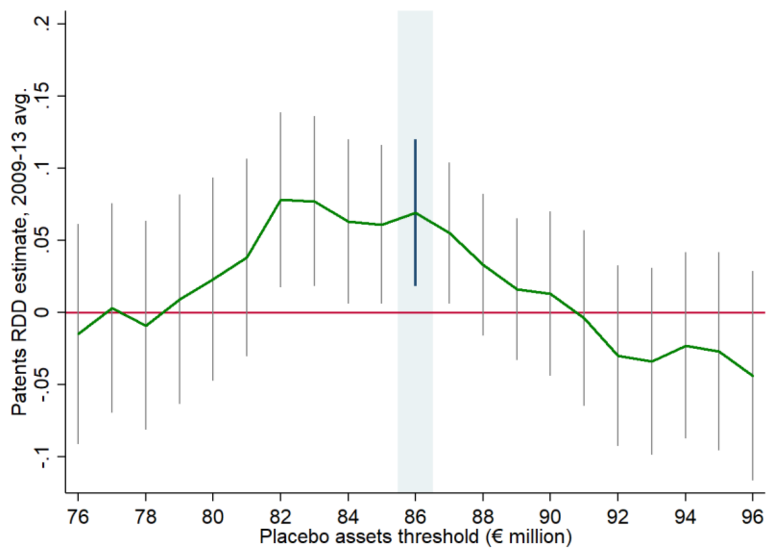
Note: The figure is produced by Calonico, Catteneo, and Titunik's (CCT) (2014) data-driven RD plot. The dependent variable is average number of patents over 2009-13. The running variable is total assets in 2007 with a threshold of €86m. Controls include fourth order polynomials of the running variable separately on each side of the threshold. Bin size for the scatter plot is €2.5m.

Figure A5. Discontinuities in average R&D over 2009-11 at placebo SME assets thresholds



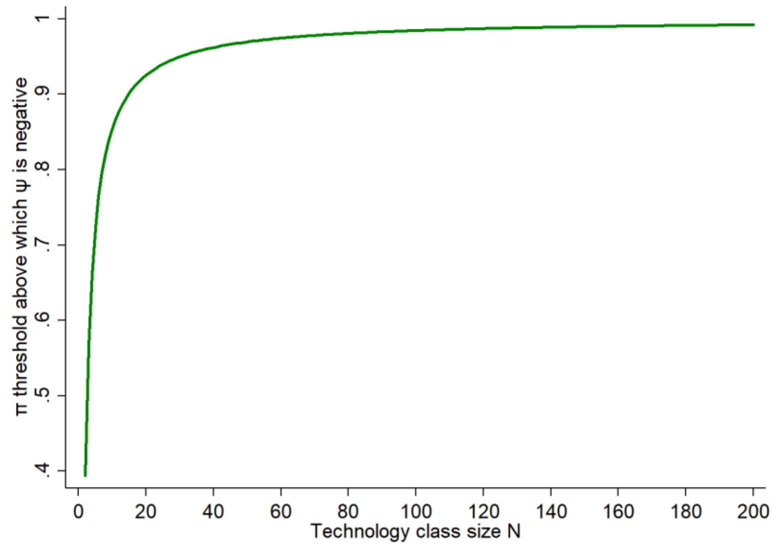
Note: This figure plots the discontinuities in average R&D expenditure over 2009-11 at different placebo assets thresholds. The coefficient at each threshold is estimated using the baseline R&D regression in equation (1). The running variable is total assets in 2007. Baseline sample includes firms with total assets in 2007 within €25m of the corresponding placebo threshold. Controls includes first order polynomials of running variable separately for each side of the placebo threshold. The grey lines indicate the 95% confidence intervals of the discontinuity estimates.

Figure A6. Discontinuities in average number of patents over 2009-13 at placebo SME assets thresholds



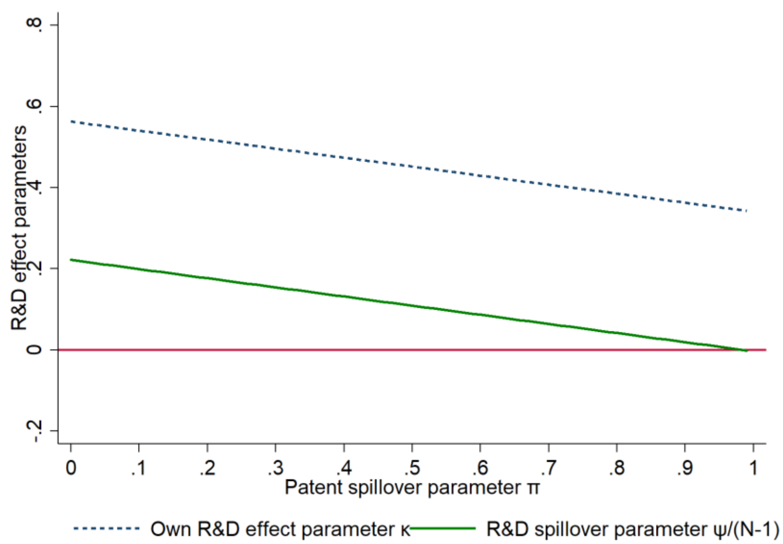
Note: This figure plots the discontinuities in average patents over 2009-13 at different placebo assets thresholds. The coefficient at each threshold is estimated using the baseline patent regression in equation (2). The running variable is total assets in 2007. Baseline sample includes firms with total assets in 2007 within €25m of the corresponding placebo threshold. Controls include first order polynomials of running variable separately for each side of the placebo threshold. The grey lines indicate the 95% confidence intervals of the discontinuity estimates.

Figure A7. Sign of R&D spillover ψ as a function of patent spillover effect π and technology class size N



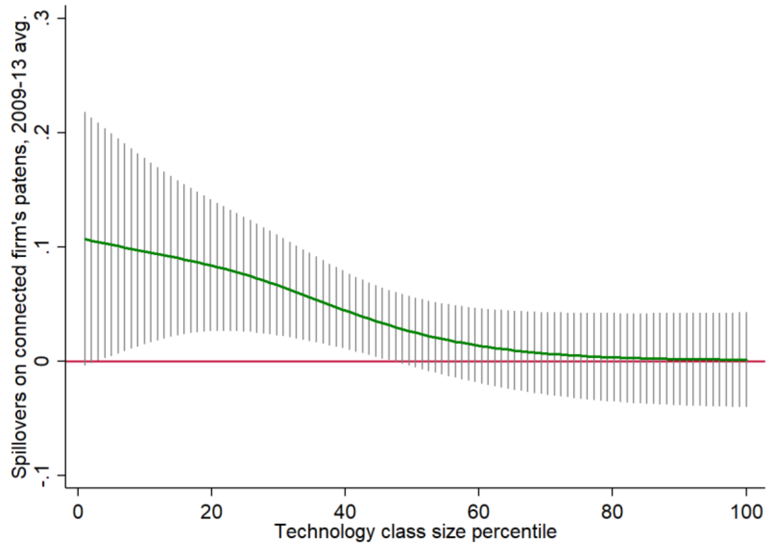
Note: Recall equation (D1) which specifies the system of technology spillovers among firms. The green curve plots the $\bar{\pi}$ (direct patent spillover parameter) threshold above which ψ (direct R&D spillover parameter) is negative at each different value N (technology class size), given equation (D2) and estimates of γ (*net* own R&D effect) of 0.563 (column 2 of Table 6) and ξ (*net* R&D spillover effect) of 0.222 (column 8 of Table 8). The area under the green curve represents the space in which ψ would be positive and vice versa. For the system to be stable, π must not exceed 1.

Figure A8. Own R&D effect κ and R&D spillover effect ψ as functions of patent spillover effect π



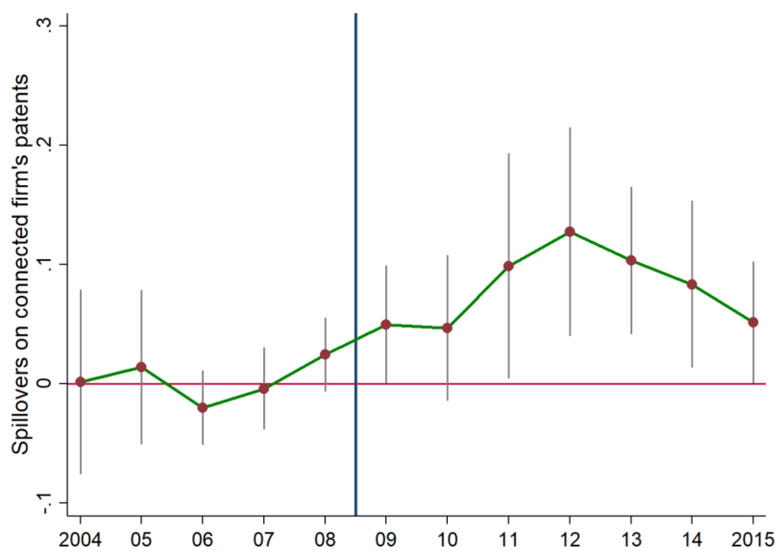
Note: Recall equation (D1) which specifies the system of technology spillovers among firms. This figure plots κ (direct own R&D effect parameter) and $\psi/(N-1)$ (direct R&D spillover parameter) as a function of π (direct patent spillover parameter) for N (technology class size) equal to 109 (i.e., "average" value of N among Table 8, column 8's sample). The calculations are based on equations (D2), and estimates of γ (*net* own R&D effect) of 0.563 (column 2 of Table 6) and ξ (*net* R&D spillover effect) of 0.222 (column 8 of Table 8). (See Appendix D.1 for further details.)

Figure A9. Spillovers on "loosely" connected firm's patents by primary patent class size



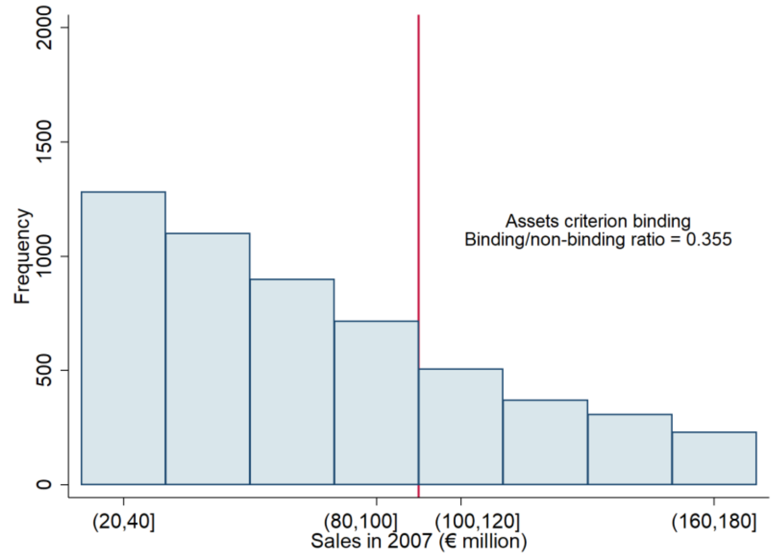
Note: This figure presents semi-parametric estimates of the spillover coefficient on "loosely"-connected firms' patents as a function of the technology class size percentile (the X-axis variable). Two firms are "loosely" connected technologically if they patent primarily in the same three-digit IPC technology class. The semiparametric estimation is based on equation (5), using a Gaussian kernel function of the X-axis variable and a bandwidth of 20% of the range (see Appendix D.4 for details). The grey lines indicate the 90% confidence intervals of the spillover coefficients.

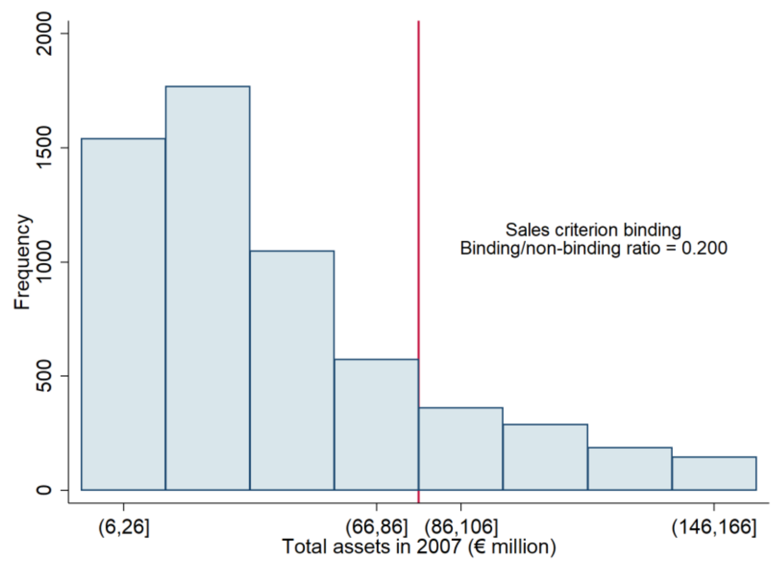
Figure A10. Evolution of R&D technology spillovers among small technology classes



Note: This figure plots the spillover coefficients estimated using equation (5) among firms in small technology classes (i.e., technology class size below 200). Additional lagged dependent control for firm *j*'s average patents over 2006-08 is included. The grey lines indicate the 90% confidence intervals of the spillover coefficients.

Figure A11. Number of firms with binding and non-binding assets and sales criteria





Note: Top figure: Sample includes firms with 2007 total assets in [€36m, €136m] and 2007 sales in (€20m, €180m]. Among them, the assets criterion is not binding for 3,998 firms with 2007 sales in (€20m, €100m], and binding for 1,419 firms with 2007 sales in (€100m, €180m]. The corresponding binding/non-binding ratio is 1,419/3,998 = 0.355. **Bottom figure:** Sample includes firms with 2007 sales in [€50m, €150m] and 2007 total assets in (€6m, €166m]. Among them, the sales criterion is not binding for 4,934 firms with 2007 total assets in (€6m, €86m], and binding for 983 firms with 2007 total assets in (€86m, €166m]. The corresponding binding/non-binding ratio is 983/4,934 = 0.200.