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

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Abstract

We present the evidence of the positive causal impacts of research and development (R&D) tax incentives on own-firm innovation and technological spillovers. Exploiting a change in the assets-based size thresholds that determine eligibility for R&D tax subsidies, we implement a Regression Discontinuity design using administrative tax data. There are statistically and economically significant effects of tax on R&D and (quality-adjusted) patenting that persist up to seven years after the change. A one percent reduction in the tax price generates 3.6% more patents. R&D tax price elasticities are large, with a lower bound of 1.1, consistent with the fact that the treated group are smaller firms that are more likely subject to financial constraints. Using our Regression Discontinuity 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

JEL codes: O31, O32, H23, H25, H32.

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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 R&D Tax Relief Scheme and did not overlap with access to other programs or taxes. Given this change, we can implement a Regression Discontinuity (RD) Design looking at the differences in innovation activity around the new SME threshold. We show that there were no discontinuities in any outcome around the threshold in the years prior to the policy change.

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] Indeed, the tax incentive could increase observed R&D without having much effect on innovation if, for example, firms relabeled existing activities as R&D to take advantage of the tax credits (e.g., Chen et al., 2016) or only expanded very low-quality R&D projects. We can also directly examine the quality of these additional innovations through various commonly used measures of patent value, such as

[1] Typical results find marginal social rates of return to R&D between 30% and 50% compared to private returns between from 7% to 15% (Hall, Mairesse, and Mohnen, 2010).
[2] Over the period 2001-11, R&D tax incentives expanded in 19 out of 27 OECD countries (OECD 2014). 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).

future citations received and the number of countries that a patent obtains protection.

We find large effects of the tax policy on R&D and patenting activity. Following the policy change, R&D more than doubled in firms below eligibility threshold, followed by about a 60% increase in patenting. There is no evidence that these innovations were of lower value. We can reject absolute elasticities of R&D with respect to its user cost of less than 1.1 with a 5 percent level of confidence.[4] Our relatively high elasticities are likely because the sub-population targeted in our design is composed of smaller firms than is typical in the literature. These firms are more likely to be financially constrained and therefore are more responsive to R&D tax credits. We confirm this intuition by showing the response was particularly strong for firms in industries that were more likely to be subject to financial constraints.[5]

Simple partial equilibrium calculations suggest that over 2006-11 the UK R&D policy induced about $2 of private R&D for every $1 of taxpayer money and that aggregate UK business R&D 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 return to R&D exceeds the private return. 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 Design specification with connected firms' patents as the outcome variable of interest. We find evidence that the R&D induced by the tax policy generated positive spillovers on innovations by technologically related firms, especially in small 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. The rest of this section offers a brief literature review; Section 2 details the institutional setting; Section 3 explains the empirical design; Section 4 describes the data; and Section 5 presents the main results. The spillover analysis is in Section 6; various extensions and robustness checks are discussed in Section 7; and some concluding comments are offered in Section 8. Online Appendices provide additional institutional detail (A), data

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 1 and 2 whereas our mean results are 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.

description (B), and econometric detail (C).

Related Literature. Most directly, our paper contributes to the literature that seeks to evaluate the causal impact of tax policies on firms' R&D. Earlier evaluations conducted at the state or macro-economic level face the problem that changes of policies likely coincide with many unobserved factors that may influence R&D. Recent studies use firm-level data and more compelling causal designs, but focus on the impact of R&D tax credits on R&D expenditures.[7] Rao (2016) uses administrative tax data and looks at the impact of US tax credits on R&D (but not other firm outcomes). 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. (2017) 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 a Regression Discontinuity 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. (2014) examine NIH grants; Ganguli (2017) looks at grants for Russian scientists and Bronzini and Iachini (2014); and Bronzini and Piselli (2014) 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.

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[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 (2014) 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.

Third, our paper also contributes to the literature on the effects of R&D on innovation (e.g., Doraszelski and Jaumandreu, 2013; Hall, Mairesse, and Mohnen, 2010 survey). We find that policy-induced R&D had a positive causal effect on innovation, with elasticities that are underestimated in conventional OLS approaches. Although there is also a large literature on R&D 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 Regression Discontinuity setting.

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. Institutional setting

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 it 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 £1.4bn in 2013 alone (Fowkes, Sousa, and Duncan, 2015).

The tax policy 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.*[13] This design feature aims at dealing with the problem that smaller companies may not be making enough profits to benefit from the enhancement rate. The refundable aspect of the scheme is particularly beneficial to firms that are liquidity

[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.

[13] Throughout we will use "tax credit" to refer to this refundable element of the scheme as distinct from the "enhanced tax deduction" element.

constrained and we will present evidence in line with the idea that the large treatment effect we observe were linked to the alleviation of such financial constraints. Large companies had a less generous deduction rate of 25% of their R&D and could not claim the refundable tax credits in the case of losses (Finance Act, 2002).

The policy used the definition of an SME recommended by the European Commission (EC) throughout most of the 2000s. This was based on assets, sales, and employment from the last two accounting years. 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 in two consecutive years.

We focus on the major change to the scheme that commenced from August 2008. The SME assets threshold was increased from €43m to €86m, the sales threshold from €50m to €100m, and employment threshold from 249 to 499.[14] Because of these changes, a substantial proportion of companies that were eligible only for the large company rate according to the old definition 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. The SME enhancement rate increased from 50% to 75%.[15] For large companies, the rate changed from 25% to 30%. The policy change induced a reduction in the tax-adjusted user cost of R&D from 0.19 to 0.15 for the newly eligible SMEs whereas the user cost for large companies was basically unchanged (see subsection 7.2 below and 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 EU 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.[16] Second,

[14] The other criteria laid down in the EC 2003 recommendation (e.g., two-year rule) were maintained in the new provision in Finance Act 2007. This Act, however, did not appoint a date on which new ceilings became effective. This date, which was eventually set for August 1st, 2008, was announced much later, on July 16th, 2008.

[15] In parallel, the SME payable tax credit rate was cut slightly to 14% (from 16%) of enhanced R&D expenditure (i.e., 24.5% of R&D expenditure) to ensure that R&D tax credit falls below the 25% limit for state aid.

[16] For the same reason, we do not exploit the discontinuity at the old SME thresholds to examine the effects of the R&D Tax Relief Scheme, either before or after the policy change. In principle, as the policy change has differential impacts on firms below and above the *old* SME thresholds, its impact could be recovered from the differences in responses (i.e., changes in R&D or patenting) by firms below the old thresholds (who remained SMEs) and firms above the old thresholds (who switched from being large companies to being SMEs), However, it is not possible to separate these effects from changes in how other confounding policies differentially affected these two groups of firms, especially in the context of the Great Recession.

identifying the impacts around newly introduced thresholds mitigates concerns that tax planning may lead to endogenous bunching of firms around the thresholds. We show that there was no bunching around these thresholds in 2007 (or earlier) and covariates were all balanced at the cut-offs. This is important, as although the policy's effective date was not announced until July 2008 (and set for August 2008); aspects of the policy were understood in 2007 so firms may in principle 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.[17] The 2007 values of firm accounting variables are therefore what we use as running variables, as they matter for the firm's SME status in 2009 by the two-year rule, but are unlikely to be affected by tax-planning incentives.

We focus on assets as the key running variable. This is one of the three determinants of SME status and, unlike sales and employment, does not suffer from missing values in the available datasets. We discuss this in detail in Section 4. In subsection 7.6, we also consider using sales and employment as the running variables, which generates qualitatively similar results.

3. Empirical strategy

Consider a simple 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 and $\varepsilon_{1i,t}$ is an error term. We use polynomials of the running variable, assets in 2007 $f_{1,t}\left(z_{i,2007}\right)$, which are allowed to be different either side of the new SME threshold ($\tilde{z}$). $E_{i,2007}$ is a binary indicator equal to one if 2007 assets are less than or equal to the threshold value and zero otherwise. The coefficient of interest β^R estimates the reduced-form effect of being below the assets threshold, and therefore more likely to be eligible for the more generous SME scheme, on a firm's R&D spending at this threshold.[18] In an RD Design, the identification assumption requires that the distribution of all predetermined variables is smooth around the threshold, which is testable on observables. This identification condition is

[17] Sluggish adjustment to policy announcements is consistent with many papers in the public finance literature (e.g., Kleven and Waseem, 2013).

[18] 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 regression 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 who do not perform any R&D (see subsection 4.1). In subsection 7.2, we discuss in detail how we adjust our reduced-form estimates to account for the "fuzziness" of $E_{i,2007}$ using available information on the SME status of R&D performing firms.

guaranteed when firms cannot *precisely* manipulate the running variable (Lee, 2008; Lee and Lemieux, 2010).[19] Under this assumption, eligibility is as good as randomly assigned at the cutoff. We reproduce regressions based on equation (1) for year-by-year outcomes, as well as their average over three post-policy years. We also estimate analogous regressions in the pre-policy years to assess the validity of the RD Design. The "new SMEs", i.e., those becoming SMEs only under the new definition, could only obtain the higher tax deduction rates on R&D performed after August 2008. Hence, to the extent that firms could predict the threshold change in early 2008 (or manipulate the reported timing of within year R&D), such companies would have an incentive to *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 assets threshold of €86m.[20] 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. Using assets in 2007 as our primary running variable thus mitigates the concern that there might have been endogenous sorting of firms across the threshold. Indeed, Figure 1 shows that firms' 2007 assets distribution is continuous around the new 2008 SME threshold of €86m. The McCrary test gives a discontinuity estimate (log difference in density height at the SME threshold) (standard error) of -0.026 (0.088) that is insignificantly different from zero. On the other hand, there appears to be some small, but also insignificant, evidence bunching in later years (see subsection 7.5).[21]

In terms of innovation outputs, we consider the following reduced-form RD equation:

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

where the dependent variable $PAT_{i,t}$ is number of patents filed by firm i in year t. We also examine the impact over a longer period from 2009 to 2015, due to the potential lag between R&D inputs

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[19] 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.

[20] In the baseline results, being mindful of Gelman and Imbens's (2014) warning against using higher order polynomials when higher order coefficients are not significant, we use a first order polynomial. We show in robustness checks that including higher order polynomials produce qualitatively similar results across all specifications.

[21] Using available data on sales and employment, similar McCrary tests also suggest that in 2007, (i) there was no bunching below the respective sales and employment thresholds, and (ii) there was no bunching below the assets threshold among firms for whom the assets threshold was binding (i.e., firms that met the employment criterion but did not meet the revenue one). The evidence further confirms that firms had not immediately manipulated their financials in response to the news of the policy change (especially when the new policy's effective date was only announced a year later, in July 2008).

and outputs. Under the same identification assumptions discussed above, $\hat{\beta}^{PAT}$ consistently estimates the causal effect of being below the asset threshold, and therefore more likely to be eligible for the more generous SME scheme at the threshold.

Thirdly, we 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) and (3) correspond to the first stage and structural equations of an RD-based IV model that estimates the impact of additional R&D spending induced by the difference in tax relief schemes on firm's patents, using $E_{i,2007}$ as the instrument for R&D. With homogenous treatment effects, the IV estimate delivers the causal effect of R&D on patents; and with heterogeneous treatment effects, it captures the causal marginal effect of policy-induced R&D on innovation outputs.[22] 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 above, 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 non-qualifying spending, such as investments in capital or managerial capabilities (even though they would want to classify as much of this spending as qualifying R&D expenditure as possible), or alternatively (ii) relabeled existing non-R&D spending as qualifying R&D expenditure 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 expense category other than qualifying R&D at the eligibility threshold in the post-policy period (in contrast to Chen et al., 2017),. This suggests that these other channels through which $E_{i,2007}$ could affect innovations and the biases they imply are unlikely to be of 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.

Appendix 3.1 shows how equations (1) and (3) can be derived from optimizing behavior of a

[22] 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.

firm with an R&D augmented CES production function and Cobb-Douglas knowledge production function. We discuss how equation (1) and (2)'s reduced-form estimates can be adjusted to derive the elasticity of R&D ad patents with respect to R&D user cost in subsection 7.2.

4. Data description

4.1 Data sources

Appendix B details our three main data sources: (1) HMRC Corporate Tax returns (CT600) and its extension, the Research and Development Tax Credits (RDTC) dataset, which provide data on the universe of UK firms and importantly include firm's R&D expenditures as claimed under the R&D Tax Relief Scheme; (2) Bureau Van Dijk's FAME dataset, which provides data on the accounts of the universe of UK incorporated firms; and (3) PATSTAT, which contains patent information on all patents filed by UK companies in the main 60 patent offices across the world.

CT600 is an administrative panel dataset provided by 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,[23] with close to 16 million firm by year observations, and contains all information provided by firms in their annual corporate tax returns. We are specifically interested in the RDTC sub-dataset, which consists of all information related to the R&D Tax Relief Scheme, including the amount of qualifying R&D expenditure each firm had in a year and the scheme under which it made the claim (SME vs. Large Company Scheme). Firms made 53,000 claims between 2000 and 2011 for a total of £5.8 billion in R&D tax relief; about 80% of the claims were under the SME scheme.

We only observe R&D when firms claim R&D tax relief. All firms performing R&D are in principle eligible for tax breaks, 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.[24] 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 SMEs reporting their R&D, so there are many missing values. Statistics provided by internal HMRC analysis indicate that qualifying R&D expenditure amounts to 70% of total business R&D (BERD).[25] Note that the

[23] The UK fiscal year runs from April 1st to March 31st, so 2001-02 refers to data between April 1st, 2001 and March 31st, 2002. In the text we refer to the financial years by their first year, so 2011-12 is denoted "2011".
[24] That is, given the ease of the process, selection into claiming R&D tax relief (conditional on having performed R&D) is unlikely to be a first order concern.
[25] There are various reasons for this difference; including the fact that BERD includes R&D spending on capital

other outcomes, most importantly patents, are observed for all firms, regardless of whether they claimed R&D tax relief or not.

CT600 makes it possible to determine the SME status of firms that claim the R&D tax relief, but not the SME status of the vast majority of firms that are *not* claiming. Employment and total assets are not available because such information is not directly 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.[26] Consequently, we turn to a second dataset, FAME, which contains all UK company accounts since about the mid-1980s. We match CT600 to FAME by an HMRC-anonymized version of company registration number (CRN), which is a unique regulatory identifier in both datasets. We merge 95% of CT600 firms between 2006 and 2011 with FAME and these firms covered 100% of R&D performing firms and patenting firms. Unmatched firms were slightly smaller but not statistically different from matched ones across various variables reported in CT600, including sales, gross trading profits, and gross and net corporate tax chargeable (see Appendix B.4).

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, between 2006 and 2011, 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 reported by 67% and 55% of firms respectively.[27] For this reason, we focus on exploiting the SME assets threshold with respect to total assets and use this as the key running variable in our baseline fuzzy RD Design reduced-form specification. In addition, FAME provides industry, location, capital investment, profits, remuneration and other financial information through to 2013, though coverage differs across variables.

We also experiment with using employment and sales to determine SME status, despite the greater number of missing values. In principle, using additional running variables should increase efficiency, but in practice (as we explain in sub-section 7.6) it does not lead to material gains in the precision of the estimates. Hence, in our main specifications, we use the assets-based criterion

investment whereas qualified 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.

[26] 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.

[27] 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.

for determining eligibility, because it allows us to cover a larger company population.[28]

Our third dataset, PATSTAT, is the largest available international patent database and 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) and the Japan Patent Office (JPO). Patents filed with the UK Intellectual Property Office are also included. To assign patents to UK-based companies we use the matching 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 select 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, which are sets of patents protecting the same invention across several jurisdictions. 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.[29]

In our baseline results, we use the number of patent families – irrespective of where the patents are filed – as a measure of the number of inventions for which patent protection has been sought. This means that we count the number of patents filed anywhere in the world by firms in our sample, whether at the UK, European or US patent office, but we use information on patent families to make sure that an invention patented in multiple jurisdictions is only counted once. Patents are sorted by application year, which tracks R&D much more closely than publication or granted dates.

Numerous studies have demonstrated a strong link between patenting and firm performance.[30] Nevertheless, patents have their limitations (see Hall et al., 2013). To tackle the problem that the value of individual patents is highly heterogeneous, we use various controls for 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.[31]

[28] It is worth noting that using only one threshold for identification in a multiple threshold policy design does not violate the assumptions for RD Design; it may just reduce the generality and efficiency of the estimates.

[29] This means that our dataset includes patents filed by foreign affiliates of UK companies overseas that relate to an invention filed by the UK-based mother company. However, patents filed independently by foreign affiliates of UK companies overseas are not included.

[30] For example, see Hall, Jaffe, and Trajtenberg (2005) on US firms; or Blundell, Griffith, and Van Reenen (1999) on UK firms.

[31] Variations of these quality measures have been used by *inter alia* Lanjouw et al. (1998); Harhoff et al. (2003); and Hall et al. (2005).

4.2 Baseline sample descriptive statistics

We construct our baseline sample from the above three datasets. Our baseline sample contains 5,888 firms with total assets in 2007 between €61m and €111m, based on a €25m bandwidth around the threshold, with 3,651 and 2,327 firms below and above the €86m SME assets threshold respectively. Our choice of bandwidth is guided by results from the Calonico, Catteneo, and Titunik (2014) robust optimal bandwidth approach, yet we still have to decide on one single bandwidth for both R&D and patent outcomes to have a consistent baseline sample.[32] Therefore, we also show robustness to a range of alternative bandwidths and kernel weights.

Our key outcome variables include (i) amount of qualifying R&D expenditure, and (ii) number of patents filed. All nominal variables are converted to 2007 prices using the UK Consumer Price Index, and all outcome variables are winsorized at 2.5% of non-zero values to mitigate the leverage of outliers.[33] In 2006-08, 259 of the firms in this 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,[34] we choose to include in our baseline sample 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.[35] For similar reason, firms who exited after 2008 are kept in the sample to avoid selection bias (as firm survival is also a potential outcome) and are given zero R&D and patents.

Table 1 gives some descriptive statistics on the baseline sample. In the 2006-08 period firms below the threshold spent on average £61,030 per annum on R&D and firms above the threshold spent an average of £93,788. After the policy change, between 2009 and 2011, these numbers changed to £80,269 and £101,917. That is, the gap in R&D spending between the two groups of firms reduced by more than 30% from £32,758 pre-policy to £21,649 after the policy change. In terms of innovation outputs, the average number of patents per annum was similar between the two groups of firms before the policy change (0.061 vs. 0.067), while post-policy, firms below the

[32] The Calonico, Catteneo, and Titunik (2014) robust optimal bandwidth for using R&D as the outcome variable is 20, and for using patents as the outcome variable is 30. Our baseline bandwidth choice of 25 is in between these two. We also implement the Imbens and Kalyanaraman (2011) optimal bandwidth approach, which yields similar results.

[33] 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.

[34] 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.

[35] 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.

SME assets threshold filed around 40% more patents than those above the threshold during 2009-13 (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 unadjusted 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 global financial crisis of 2008-09 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 (as firms do not differ across the threshold), whereas the D-in-D estimator does not.

Indeed, Table 2, which reports the balance of pre-determined covariates conditional on the running variable, shows that firms right below and above the threshold are 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. Main results

5.1 R&D results

Table 3 examines the impact of the policy change on R&D (equation 1). The key explanatory variable is the binary indicator for whether the firm's total assets in 2007 did not exceed the new SME assets threshold of €86m, and the running variable is the firms' total assets in 2007. The baseline sample includes all firms with total assets in 2007 between €61m and €111m, including non-R&D-performers. Looking at each of the two pre-policy years 2006 and 2007 and the transition year 2008 in columns 1-3, we find no significant discontinuity in R&D at the threshold. In the next three columns, we observe that from 2009 onward, firms just below the SME threshold had significantly more R&D than firms just above the threshold. 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 a conservative estimate (£60,400), especially given the positive sign of the coefficient in columns 1-3. A similar approach is to directly control for pre-policy R&D in column 10, which yields a near identical estimate of £63,400 that is significant at the 5% level. These unadjusted reduced-form coefficients are not far below the pre-policy average annual R&D of £74,000, suggesting that the policy had a substantial impact from an economic as well as statistical perspective. Furthermore, it is worth noting that the effect was larger among (if not driven by) firms with fewer than 500 in employment in 2007, for whom the assets criterion was binding (Table A3 Panel A).[36]

Figure 2 shows the visible discontinuity in R&D at the SME assets threshold, despite the large bin size due to data disclosure restriction.[37] Unsurprisingly, larger firms with more assets do more R&D as shown by the upward sloping regression lines, but right across the threshold there is a sudden jump in R&D consistent with a policy effect. The magnitude of the jump corresponds to the estimate in column 8 of Table 3. 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. Figure A3, which plots the resulting coefficients and their 95% confidence interval against the corresponding thresholds, shows that the estimated discontinuities in 2009-11 R&D peaks at €86m, while they are almost not statistically different from zero anywhere else.[38] That is, the jump exists only at the true SME threshold, as the result of the 2008 policy change.

Our results are robust to a wide range of robustness tests (Table A4). First, if we add a second order polynomial to the baseline specification of column 8 in Table 3, the discontinuity (standard

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[36] Panel A (Panel B) of Table A3 reports the key R&D and patent results among 2,246 (845) firms with fewer than (at least) 500 in employment in 2007 (conditional on non-missing 2007 employment data). While the 2008 policy change generated large jumps in R&D and patents at the assets threshold among firms for whom the assets criterion was binding (Panel A), it had no similar effects on the other set of firms (Panel B).

[37] 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.

[38] If we adjust the pseudo-threshold samples to not overlap with the true threshold, then all the resulting coefficients are small and not statistically different from zero. For example, using a pseudo threshold of €71m with as an upper bound the true threshold of €86m and as a lower bound €46m (€25m below the pseudo threshold) yields a coefficient (standard error) of -8.0 (38.0), and using a pseudo threshold of €101m with as a lower bound the true threshold of €86m and as an upper bound €116m (€25m above the pseudo threshold) yields -53.1 (85.1) (compare to that of 123.3 (52.1) at the true threshold).

error) is larger at 189.9 (84.7).[39] Second, the results are robust to alternative choices of sample bandwidths and kernel weights.[40] Third, the discontinuity remains significant when we add industry and/or location fixed effects or use different winsorization or trimming rules. Fourth, we obtain statistically significant effects of comparable magnitude when using count data models instead of OLS.[41] Finally, we estimate the same specification as in Table 3 using survival as the dependent variable and find an insignificant coefficient.

5.2 Patent results

We now turn to our results on patents, which is the key outcome of interest. Table 4 reports the patent RD regressions (equation 2) using the same specification and sample as Table 3. As with R&D, the first three columns show no significant discontinuity around the threshold for 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 (columns 4-10 of Panel A).[42] Although we will focus on the 5 years from 2009 to 2013 (columns 5-7 in Panel B) as our baseline "post-policy period" for subsequent patent analyses, the results are qualitatively similar if we use the 2009-11 average (columns 2-4) or 2009-15 average (columns 8-10). According to column (5) of Panel B, there is an average discontinuity estimate of 0.069 extra patents per year for firms below the policy threshold. The corresponding coefficient for the pre-policy period is less than half the size and statistically insignificant (column 1), and this difference between pre- and post-policy discontinuity estimates is even more stark among firms for whom the assets criterion was binding (Table A3 Panel A). If we use the more-conservative before-after or lagged-dependent variable-specifications, the discontinuity estimates are 0.042 and 0.049 (columns 6 and 7). Again, these coefficients are sizeable in comparison with the pre-policy mean patents of 0.064. Figure 3 illustrates the discontinuity in the total number of patents filed over 2009-13, which corresponds to the estimate in column 5 of

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[39] Adding a third order polynomial also yields a similar estimate and we cannot reject that the higher order terms are jointly zero.

[40] This includes using Epanechnikov or triangular kernel weights, narrower bandwidths of €15m or €20m, or larger bandwidths of €30m or €35m. For larger bandwidths, we (i) add a second order polynomial to improve the fit (the coefficients on the second order assets terms are significant for both bandwidths), or (ii) use triangular kernel weights. All specifications yield statistically significant discontinuity estimates of comparable magnitude to our baseline result in column 8 of Table 3.

[41] We do this to allow for a proportionate effect on R&D (as in a semi-log specification). Using a Poisson specification yields coefficient (standard error) of 1.31 (0.49) and using a Negative Binomial specification yields 1.22 (0.49).

[42] These statistically significant discontinuity estimates decrease in magnitude gradually over time, as 2007 assets is a progressively weaker predictor of firm's SME status. Part of this is because firms below the assets threshold in 2007 grew and eventually were no longer SMEs (Table 9). In Table A14, we report evidence of substantial policy-induced increase in employment that is consistent with this explanation.

Table 4 Panel B. As with R&D there is clear evidence of the discontinuity in innovations at directly the point of the SME threshold for R&D tax relief purpose, but not anywhere else (Figure A4).

This is a key result: nothing in the R&D tax policy required a firm to show any patenting activity either in filing for R&D tax subsidies or in any auditing by the tax authority of how the R&D money is spent. Therefore, there was no administrative pressure to increase patenting. It may seem surprising that we observe a response in patenting as soon as 2009, but patent *applications* are often timed quite closely to research expenditures.[43] 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. Finally, we run all the robustness and validity tests discussed for the R&D equation on the patent regressions. These include adding higher order polynomial controls or industry and/or location fixed effects, using alternative choices of sample bandwidths and kernel weights, using different winsorization or trimming rules, employing count data models instead of OLS (Table A5), and employing pseudo SME thresholds (Figure A4). The increase in patenting among firms below the SME threshold remains robust across these alternative specifications and peaks only at the true threshold, further confirming the validity of the RD Design and the policy effect on innovation.

As patents vary widely in quality, one important concern is that the additional patents induced by the policy could be of lower value. Table 5 investigates this possibility by considering different ways to account for quality. Column 1 reproduces our baseline result of patent counts. Column 2 counts only patents filed in the UK patent office, column 3 those filed at the European Patent Office (EPO) and column 4 those filed at the USPTO. Since filing at the EPO and USPTO is more expensive than just at the local UK office,[44] these patents are likely to be of higher value. It is clear that the policy also had a significant and positive effect on the high value patents. Although the coefficient is larger for UK patents, so is the pre-policy mean. Focusing on the relative effect (the RD coefficient divided by the pre-policy mean of the dependent variable) reported in the final row, the effects 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). Column 5 generates this approach by weighting patents by

[43] 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.

[44] 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).

patent family size, i.e., the total number of jurisdictions in which each invention is patented, which generates a significant relative effect of around 0.9.

Column 6 of Table 5 weights patents by future citations, which yields a positive and significant estimate.[45] However, we need to keep in mind that our data is very recent for forward citation count purpose, so the elasticity is less meaningful.[46] To address this issue, we use the number of patents that are in the top citation quartile (in their technology class by filing year cohorts) in column 7. Here we obtain a relative effect of 1.0, very similar to the baseline. Finally, we examine heterogeneity with respect to technology segment looking specifically at chemicals (including biotechnologies and pharmaceuticals) in column 8 and information and communication technologies (ICT) in column 10. These sectors do produce somewhat larger relative effects (both around 1.7 compared to 1.0 in other sectors), but columns 9 and 10 show that our results are not all driven by these technologically dynamic sectors.

In summary, there is no evidence from Table 5 of any major fall in innovation quality due to the policy's inducing only marginal R&D patents.[47] Instead, it appears to robustly raise both patent and quality-adjusted patent counts (but not necessarily average patent quality) across many measures of patent quality.

5.3 IV results for the Knowledge Production Function

Table 6 estimates knowledge production functions (IV patents regressions) where the key right-hand-side variable, R&D, is instrumented by the discontinuity at the SME threshold (equation 3).[48] As discussed in Section 3, the exclusion restriction, which requires that the instrument affects innovations only through qualifying R&D, is likely to hold in our setting given the lack of

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[45] 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 only quality-adjusted patent counts (i.e., the policy did induce meaningful patents/innovations of some value).

[46] Patents are typically published 18 months after the application filing date, and it takes an average of 5 years after the publication date for a patent to receive 50% of its lifetime citations. As pre-policy patents had had more time to accumulate citations compared to post-policy patents, we would expect a lower "elasticity", which is also less meaningful. The same issue extends to patent family counts, as pre-policy patents also had had more time to be filed in more jurisdictions, which explains the lower elasticity in column 5.

[47] We also look at many other indicators of quality such as weighting by (i) patent scope (i.e., the number of patent classes a patent is classified into), (ii) the originality index (a measure of how diverse a patent's backward citations are), and (iii) generality index (a measure of how diverse a patent's forward citations are). We also count the number of patents that are in their respective cohorts' top quality quartile as measured by these indices. All of these quality-weighted and top-quality-quartile patent counts yield positive and significant estimates with implied proportionate effects comparable to our baseline patent result (Table A7 Panel A). Separately, we look at the number of patents subsequently granted (rather than all applications); this similarly yields a positive and significant estimate.

[48] In the corresponding IV model, the first-stage regression of R&D on the below-assets-threshold instrument is reported in column 8 of Table 3, and the reduced form regression of patents on the same instrument is reported in column 5 of Table 4 Panel B.

evidence of policy effect on other non-qualifying expense categories (Table A13).[49] Column 1 presents the OLS specification showing a positive association between patents and R&D. Column 2 reports a larger IV coefficient, which implies that one additional patent costed on average \$2.4 million (= 1/0.563 using a \$/£ exchange rate of 1.33) in additional R&D. At the pre-policy means of R&D and patents (£0.074m and 0.064 respectively), this implies an elasticity of patents with respect to R&D of 0.65 for our IV estimates (compared to 0.24 for OLS). If we also control for average pre-policy patents over 2006-08 as in column 7 of Table 4 Panel B, the IV estimate decreases from 0.56 to 0.43 (Table A6 Panel B) implying an elasticity of 0.50.

The next columns of Table 6 compare UK, EPO, and US filings. All indicate significant effects of addition 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), reflecting the fact that only inventions of higher value (and costs) are typically patented outside of the UK.[50] These figures are broadly in line with the existing estimates for R&D costs per patent of \$1 to \$5 million.[51] We again subject these IV regressions to the robustness tests discussed for R&D and patent regressions to show that the magnitudes are robust (Table A6).

The fact that the IV estimates are larger than the OLS ones is consistent with the LATE interpretation that the IV specification estimates the impact of additionally induced R&D on patents among complier firms, namely those increased their R&D because of the policy. If these firms were more likely to be financially constrained, they were more likely to have higher-return R&D projects, which they could not have taken without the policy. Some direct evidence for this hypothesis is presented in Table 7. We calculate the average cash holdings to capital ratio in each three-digit industry in the pre-policy period using the population of UK firms.[52] All else equal we expect industries with higher cash-to-capital ratios to be less financially constrained. In columns

[49] Table A13 reports statistically insignificant discontinuities across multiple different (non-R&D) expense categories, among both all baseline firms and only R&D-performing firms. 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 relabelling is unlikely to be a first order concern in our context. Furthermore, relabelling, had it happened, could not explain the effect the policy had on patents, and would only bias equation 6's IV estimate downward (as it would exaggerate the policy's effect on R&D).

[50] 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.

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

[52] This ratio is computed using FAME data for the universe of UK firms between 2000 and 2005. 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 industry levels, or using cash flow instead of cash holding, yields qualitatively similar results.

1 and 4 of Table 7, we fully interact all right-hand-side variables in our baseline specification with the industry cash-to-capital measure. The interaction terms indicate that the treatment effects on both R&D and patents are significantly larger for firms in financially constrained sectors. The other columns split sample into industries below and above the mean of the financial constraints measure (instead of using it as a continuous measure), which again show that the policy had positive and significant effects only on the firms who were more likely to be financially constrained.[53] In addition, we also calculate the Rajan and Zingales (1998) index of industry external-finance dependence and find qualitatively similar results (Table A19).

6. R&D technology spillovers

The main economic rationale given for more generous tax treatment of R&D is that there are technological externalities, so the social return to R&D exceeds the private return. 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 Design specification with connected firms' patents as the outcome variable of interest (see Dahl, Løcken, and Mogstad, 2014, for a similar methodological approach in a different context).

For this exercise, we consider two firms to be technologically connected if (i) most of their (pre-2008) patents are in the same three-digit technology class and (ii) the firms have an above median Jaffe (1986) technological proximity (i.e., 0.75) between themselves.[54] The first criterion allows us to allocate each dyad to a single technology class, whose size, as we will show, determines the strength of the spillovers. However, as two firms sharing the same primary technology class could still have very different patent portfolios, especially when they are both highly diversified, we further refine the definition of technological connectedness with the second criterion. Relaxing either criterion, or imposing more restrictions, does not affect our qualitative findings.

We then construct a sample of all firm i and j dyads ($i \neq j$) in which (i) firm i is within our baseline sample of firms with total assets in 2007 between €61m and €111, and (ii) 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. There are 203,832 possible such dyads

[53] The IV estimate for the effect of R&D on patents (similar to Table 6 column 2) in the subsample of more financially constrained firms is 0.602, significant at 5% level, and larger than the baseline estimate of 0.563. This is consistent with our hypothesis that the returns to R&D are higher among more financially constrained firms.

[54] Let $F_i = (F_{i1}, \dots, F_{i\Upsilon})$ be a $1 \times \Upsilon$ vector where $F_{i\tau}$ is firm i's fraction of patents in class τ. Firms i and j's Jaffe proximity is $\omega_{ij} = F_i F_j' / [(F_i F_i')^{\frac{1}{2}} (F_j F_j')^{\frac{1}{2}}]$, the uncentered angular correlation between F_i and F_j. This equals 1 if firms i and j have identical patent technology class distribution and zero if the firms patent in entirely different technology classes. Our baseline firms patent primarily in 91 technology classes, out of 123 available three-digit IPC classes.

in our data, covering 547 unique firm i's and 17,632 unique firm j's in 91 different technology classes. For ease of exposition, we from now on call firm i the "baseline firm" and firm j the "connected firm."

Our reduced-form spillover specification estimates the reduced-form impact of baseline firm i's eligibility for the SME scheme in terms of the assets rule (i.e., being below or at the SME assets threshold) on connected firm j's average patents over 2009-13:

$$PAT_{j,09-13} = \alpha_4 + \theta E_{i,2007} + f_4(z_{i,2007}) + g_4(z_{j,2007}) + \varepsilon_{4ij}. \tag{4}$$

Each observation is a pair of a baseline firm and a connected firm; $PAT_{j,09\text{-}13}$ is the connected firm's average patents over 2009-13; $\boldsymbol{E_{i,2007}}$ is the baseline firm's threshold indicator in 2007; and $\boldsymbol{f_4(z_{i,2007})}$ and $\boldsymbol{g_4(z_{j,2007})}$ are polynomials of baseline and connected firms' total assets in 2007. As discussed in section 3, $\boldsymbol{E_{i,2007}}$ is as good as random in the RD Design and therefore it is conditionally uncorrelated with connected firm j's characteristics, including its eligibility for the SME scheme, under mild sufficient conditions.[55] This allows us to interpret $\boldsymbol{\hat{\theta}}$ as a consistent estimate of the causal impact of baseline firm i's likely-eligibility on connected firm j's innovations.

In addition, we also estimate the following IV specification:

$$PAT_{j,09-13} = \alpha_5 + \xi R_{i,09-11} + f_5(z_{i,2007}) + g_5(z_{j,2007}) + \varepsilon_{5ij} \tag{5}$$

using $\boldsymbol{E_{i,2007}}$ as the instrument for R&D by baseline firm $\boldsymbol{R_{i,09-11}}$ as in equation 3. The exclusion restriction requires that the discontinuity-induced random fluctuations in the baseline firm's assets-based eligibility would only affect the connected firm's patents through spillovers from the baseline firm's innovation activities. Under this additional exclusion restriction, assumption equation 5 consistently estimates the magnitude of the spillovers. Standard errors are clustered by baseline firm to address the fact that the residuals may be correlated among firm technologically connected

[55] To be precise, 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 $\lim_{z_i \to 86-} \mathbb{E}[U_{j(i)}|E_i = 1] = \lim_{z_i \to 86+} \mathbb{E}[U_{j(i)}|E_i = 0]$, 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 $g_4(z_{j,2007})$ (or $E_{j,2007}$) 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 $z_{j,2007}$). Our results are robust to dropping this additional $g_4(z_{j,2007})$ control, or to adding additional control for $E_{j,2007}$.

to the same baseline firms.[56]

Column 1 of Table 8 reports the reduced-form spillover regression using the full sample of baseline firm-connected firm dyads, which yields a small and statistically insignificant coefficient. However, we expect spillovers to have measurable impact only in small-enough technology classes, where a single firm has a good chance of affecting the technological frontier in the field and thus other firms' innovations. 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. Column 2 tests this by fully interacting the terms in equation 4 with the size of the dyad's primary technology class. The resulting interaction term is negative and statistically significant at the 5% level, confirming our hypothesis that spillovers are larger in smaller technology classes. Figure 5 presents this result visually by plotting the spillover coefficients by the size percentile of the dyad's primary technology class,[57] which yields a downward sloping curve.

Guided by Figure 5, we split the full sample of firm dyads by the size of the dyad's primary technology class (at 200, which is the 40th percentile). The subsample of small primary technology classes includes 2,093 dyads of 67 baseline firms and 1,190 connected firms in 36 technology classes. The reduced-form spillover coefficient in this subsample (column 4) is positive and weakly significant despite the small sample size, and an order of magnitude larger than in the large technology classes in column 3. The presence of positive R&D spillovers on innovations only in small technology classes is robust to a range of robustness tests, including (i) additionally controlling for firm *j*'s likely-eligibility for the SME scheme (column 5),[58] (ii) extending the definition of technological connectedness to all dyads patenting primarily in the same three-digit technology class (column 6),[59] and (iii) examining the evolution of spillovers over alternative post-policy periods.[60]

[56] All our key results remain statistically significant (although the coefficients are expectedly less precisely estimated) under the more conservative clustering scheme by the dyad's shared primary technology class.
[57] This graph is estimated semi-parametrically: the spillover coefficient at each technology class size percentile (the X-axis variable) is obtained from the regression specified in equation 4, weighted by a kernel function at that percentile point (see Appendix C.1).
[58] As discussed earlier, technically we do not have to control for possible direct policy effect on firm *j* in the RD Design with $E_{j,2007}$. Empirically, the spillover point estimate in column 5 is close to the baseline point estimate in column 4. Separately, we find that the spillover estimate is larger among firms *j* that were above the eligibility threshold, suggesting that spillovers and direct policy effect are substitutes.
[59] Relaxing the definition of technological connectedness expectedly results in smaller spillover estimates, even in proportionate terms. More importantly, we observe the same pattern that spillovers are large and significant only in small technology classes (Figure A7). Similarly, extending the definition of technological connectedness to all dyads whose Jaffe (1986) technological proximity is above 0.75 yields spillover coefficient (standard error) of 0.177 (0.070) among 32,635 dyads in small technology classes (as determined by the baseline firm's primary technology class).
[60] Using patent data through 2015 gives a coefficient (standard error) of 0.198 (0.099) compared to 0.196 (0.097) in column 4 which is through 2013. They fall to 0.170 (0.099) if we go through only 2011 and are insignificant in the pre-policy change years.

In the last column of Table 8, we present the IV specification using the subsample of small technology classes. The 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 term of magnitudes, the spillover estimate is about 40% (= 0.22/0.56) of the direct effect of policy-induced R&D on own patents (column 2 of Table 6).

Appendix C discusses a number of robustness tests of the spillover results, such as implementing Bloom, Schankerman, and Van Reenen (2013)'s methodology and examining business stealing effects of rival R&D competition. The robustness of the results in Table 8 and this Appendix provides evidence that policy-induced R&D has a sizable positive impact on innovation outputs of not only the firms directly receiving R&D tax relief but also other firms in similar technology areas. To our knowledge, this paper is the first to provide RD estimates of technology spillovers.

7. Extensions and robustness

7.1 Intensive versus extensive margins

The additional amount of R&D could come from firms that would not have done any R&D without the policy change (i.e., the extensive margin) or from firms which would have done R&D, although in smaller amounts (i.e., the intensive margin). In Table A8, we estimate the baseline RD regression using dummies for whether the firm performs R&D or files patent as outcome variables and find evidence of extensive margin effects only for patent outcomes. Alternatively, we split the baseline sample by firms' pre-policy R&D and patents in Table A9, and by industry pre-policy patenting intensity in Table A10. Both exercises show that firms and sectors already engaged in innovation activities have the strongest responses to the policy change. These results provide strong evidence that the policy does not materially affect a firm's selection into R&D performance but works mostly through the intensive margin. In other words, the policy appears to mostly benefit firms that are already performing R&D and filing patents in the pre-policy period, which then helps increase these firms' chances of continuing to have patented innovations in the post-policy period.

We also split the baseline sample into firms that made some capital investments in the pre-policy period, and firms that did not (Table A12). The policy effects on R&D and patents are larger among firms that had invested, suggesting that current R&D and past capital investments are more likely to be 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, 2014).

7.2 Magnitudes 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)? We define the elasticity as the percentage difference in R&D capital with respect to the percentage difference in the tax-adjusted user cost of R&D. Given the large policy-induced R&D increase in our setting, we calculate the percentage difference relative to the midpoint instead of either end points, following the definition of the arc elasticity measure.[61] Specifically, the tax-price elasticity of R&D ($\eta_{R,\rho}$) is given by:

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

where ρ_{SME} and ρ_{LCO} are the firm's tax-adjusted user cost of R&D under the SME and the large companies ("LCO") schemes, and R_{SME} and R_{LCO} are the firm's corresponding R&D.[62]

Deriving the percentage difference in R: To obtain estimates of the treatment effects of the difference in tax relief schemes on R&D (i.e., $R_{SME} - R_{LCO}$) and patents, we need to scale $\widehat{\beta^R}$ and $\widehat{\beta^{PAT}}$ by how sharp $E_{i,2007}$ is as an instrument for a firm's actual eligibility as $E_{i,2007}$ does not perfectly predict firm i's post-policy SME status, $SME_{i,t}$. We estimate this "sharpness" (λ) using the following equation:

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

Equations 6 and 1 correspond to the first stage and reduced form equations in a fuzzy RD Design that identifies the effect of the change in the tax relief 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 no R&D (we do not have enough information in our data on sales and employment to determine their eligibility with reasonable precision). Therefore, we can only estimate equation (6) on the subsample of R&D performing firms.[63] Selection into this subsample by R&D performance raises the concern whether the resulting $\widehat{\lambda}$ is a consistent estimator of the true λ in the full baseline

[61] Calculating the percentage difference relative to one end point vs. the other end point yields very different results when the difference between the two points is large. Alternatively, we define the elasticity as the log difference in R&D capital with respect to the log difference in the tax-adjusted user cost of R&D: $\eta = \frac{\ln(R_{SME}/R_{LCO})}{\ln(\rho_{SME}/\rho_{LCO})}$, which yields quantitatively similar elasticity estimates (Table A16).

[62] 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 A).

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

sample, which includes non-R&D performers. In Appendix A.4 we prove that a sufficient condition for $E(\widehat{\lambda}) = \lambda$ is that the SME-scheme eligibility does not increase firm's likelihood of performing R&D compared to being ineligible, which is the case in our setting as shown in subsection 7.1. In this case, the composition of eligible and non-eligible firms below and above the threshold in the estimation sample would be the same as in the full baseline sample. As a result, we are able to derive $\frac{\widehat{\beta^R}}{\hat{\lambda}}$ and $\frac{\widehat{\beta^{PAT}}}{\hat{\lambda}}$, in which $\widehat{\beta^R}$ and $\widehat{\beta^{PAT}}$ are estimated from the full baseline sample and $\hat{\lambda}$ the R&D performing sample, as consistent estimators of the causal effect of tax policy change on R&D and patents at the threshold. Finally, we retrieve these estimators' empirical distributions and confidence intervals using a bootstrap procedure.

Table 9 reports the "first-stage" SME-status RD regressions of equation 6 using the baseline specification and the subsample of R&D performing firms in each respective year.[64] 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 post-policy years, even though the instrument's predictive power decreases over time, as we would expect. 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 on SME status of 0.353 (column 5) as the baseline estimate of λ in equation 6. Table 3 column 9's R&D discontinuity estimate of £60,400 then implies a causal annual treatment effect of £60,400/0.353 = £171,200.[65] Together, these estimates yield a percentage difference in R&D of 1.07.[66]

<u>*Deriving percentage difference in ρ:*</u> We calculate the tax-adjusted user cost, ρ_f, based on the actual design of the R&D Tax Relief Scheme (see Appendix A.5 for more details):

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

where sub-script $f \in \{SME, LCO\}$ denotes whether the firm is a smaller (*SME*) or larger company (*LCO*), A is the value of R&D tax relief, τ is the effective corporate tax rate, r is the real interest rate, and δ is the depreciation rate. We calculate A separately for the deduction regime and the

[64] 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 A16.
[65] 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.
[66] That is, $\frac{R_{SME} - R_{LCO}}{(R_{SME} + R_{LCO})/2} = \frac{171.2}{(171.2+74.0+74.0)/2} = 1.07$.

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.[67] 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.[68]

Deriving $\eta_{R,\rho}$: 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 use $\widehat{\beta^R}$ estimated from the same subsample used to estimate $\hat{\lambda}$ (Table A16 rows 1 and 7). The same calculations yield an elasticity of patents with respect to R&D user cost of 3.6.[69] These elasticities estimates are substantially higher than the typical values of between one and two found in other studies. Note that 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 our view, a better way to think of these estimates is to consider the empirical distribution. We perform a bootstrap procedure with 1,000 replications where 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.[70] Table A17 Panel A summarizes the results, which imply that, any R&D tax-price elasticity lower than 1.1 can be rejected with a 5% level of confidence in our setting.

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

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[67] The value of the tax relief (i) in the deduction case is $A_{d,f} = \tau_f(1 + e_f)$ where e_f is the enhancement rate, (ii) in the payable credit case is $A_c = c(1 + e)$ where c is the payable tax credit rate. 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.

[68] We set the real interest rate r to 5% and depreciation rate δ to 15%. As $(r + \delta)$ cancels out in the percentage difference between ρ_{SME} and ρ_{LCO}, the values of these parameters do not affect the final tax-price elasticity estimate.

[69] The patent treatment effect derived from Table 4's baseline patent discontinuity estimate of 0.042 (Panel B column 5) is 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 $\widehat{\beta^{PAT}}$ estimated from the subsample used to estimate $\hat{\lambda}$ yields an elasticity of patents with respect to R&D user cost of 2.9 (see Table A16 rows 7 for details).

[70] 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.

financially constrained and thus likely to be more responsive to R&D tax incentives. Many 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 who are likely to be financially constrained (Table 7).[71] Finally, note that the new SME thresholds were introduced in the Global Financial Crisis where *all* firms were more likely to be credit constrained. Although our RD Design is robust to this, this may limit external validity. However, it is worth pointing out that the tax effect on R&D are strong as late as 2011 (and patents as late at 2015), well after the end of the credit crunch.[72]

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"). The details of the calculations are in Appendix A.6, and we only summarize the key results of the analysis here.

Our 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.[73] During this period, annually, £302m of Exchequer costs generated £991m additional R&D in the SME scheme (and £660m of costs generated £992m additional R&D in the large company scheme). This translates into an aggregate "value for money" ratio of about 2.1.

Figure 4 shows estimates of the counterfactual business R&D (BERD) to GDP ratio in the absence of the tax relief scheme. It is striking that since the early 1980s UK BERD became an increasingly small share of GDP, whereas it generally rose in other major economies. Our analysis

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[71] On the other hand, using the method above we calculate the user cost elasticity for financially *unconstrained* firms to be about 1.3, which is much closer to the existing literature that has focused on larger firms, such as those in Compustat (see Table A16 row 9 for details).

[72] Finally, it is also worth noting that 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), as we do not observe SME_i and 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 $\left|\frac{E(\Delta R_i)}{E(\Delta \rho_i)}\right| > \left|E\left(\frac{\Delta R_i}{\Delta \rho_i}\right)\right|$.

[73] 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. Note that for the SMEs, we use the median elasticity estimate of 4.0 in our calculations, and for the large companies, we use the lower-bound elasticity estimate of 1.1.

suggests that this decline would have continued were it not for the introduction and extension of a more generous fiscal regime in the 2000s.[74] Business R&D would have been 13% lower over the 2006-11 period (total BERD is larger than tax qualifying R&D).

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 technological 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.

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

We examine if the tax policy generated changes in other aspects of firm performance through to 2013 (Table A14). We again use the baseline specification but use (i) sales, (ii) employment, (iii) capital, and (iv) Total Factor Productivity (TFP) as the outcome variables.[75] Panel B reports sizable, robust, and growing estimates of the policy impact on employment over 2009-13, consistent with a dynamic in which firms increase R&D, then innovate, and then grow larger. In Panel A, estimates are less precise but exhibit similar pattern, suggesting that the policy also have 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. Finally, we examine if more innovations translate into higher productivity by computing and estimating the policy impact on TFP (Panel D).[76] Similar to Panel A, the resulting estimates, although noisy, are substantially larger in the post-policy years, especially in comparison to the pre-policy estimates of close to zero.

These results should be interpreted with caution. As discussed above, there are many missing values on accounting values of 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 affects other measures of size and productivity as well as innovation.

[74] The trend annual decline in business R&D intensity was 0.0190% between 1981 and 1999. We estimate that in the absence of the policy change the decline would have continued at 0.0195% a year 1999 to 2012.
[75] We also include two-digit industry fixed effects to absorb across-industry heterogeneity in production technology. Our results are qualitatively similar without these fixed effects.
[76] We compute TFP by estimating a production function using the Olley and Pakes (1996) method, based on value added (calculated as sales minus imputed materials), capital, and wages, and at two-digit industry level. We also compute alternative TFP measures, including Olley-Pakes TFPs based on alternative measures of production inputs and outputs, and Solow-residual TFPs. All measures give qualitatively similar results.

7.5 Bunching at the threshold in later years

As discussed in Section 3, we chose total assets in 2007 as our primary running variable to avoid potential endogenous sorting of firms across the threshold once the policy effective date was announced in 2008. We test the validity of our primary running variable choice and our concern by performing the McCrary test for each year from 2006 to 2011,[77] which estimates the discontinuity in firms' total assets distribution at the SME threshold of €86m. The respective McCrary tests for 2006 and 2007 confirm that firms did not manipulate their total assets to benefit from the SME scheme before 2008.[78] On the other hand, there is some graphical evidence of firms' bunching right below the €86m from 2009 onward (consistent with rational responses to the policy) although they are small and insignificant. Finally, Figure A5 pools together the two years before the policy change (2006-07) and Figure A6 the three years after the change (2009-11). Endogenous sorting does seem to happen, but only after the policy became effective.[79]

7.6 Exploiting other elements of the SME definition

We also ran RD regressions using other elements of the SME definition (sales and employment) to estimate the impacts of the policy (Table A15). We must interpret these results with caution because, as noted above, there are many missing values on sales and especially employment. Furthermore, we also 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.[80]

As expected, while we still find positive effects on R&D and innovation outputs using the sales or employment criterion, these effects are not always statistically significant. 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 discontinuity estimate to pre-policy mean ratios for R&D using assets, sales, and employment

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[77] 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.

[78] The log differences in density height at the SME threshold in 2006 and 2007 are not statistically different from zero, with coefficients (standard errors) of 0.029 (0.065) and -0.026 (0.088) respectively.

[79] 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 of R&D on patents (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.

[80] The binding/non-binding ratio (i.e., the number firms for which the criterion binds divided by the number of firms for which the criterion does not bind) for the *assets* criterion is 0.36, while the same ratio for the *sales* criterion is only 0.20 (see Appendix B.6 for further details).

criteria are 1.67, 1.16, and 0.41 respectively, and the same set of ratios for patents are 1.09, 0.31, and 0.41.[81] We also examined whether combining the different SME criteria could increase the efficiency of our estimates, but found no significant improvement.[82]

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. We address this issue by exploiting a change in the UK R&D tax regime in 2008, which raised the size threshold determining whether a firm was eligible for the more generous SME tax relief scheme. This enables us to implement an RD Design and assess the impact of the policy on R&D and innovation (as measured by patenting). Using total assets in the pre-policy period of 2007, we show that there is no evidence of discontinuities around the threshold prior to the policy, which is unsurprising as the new threshold was only relevant for the R&D Tax Relief Scheme and not for other programs targeting SMEs.

The policy caused an economically and statistically significant increase in patenting (even after quality adjusting) and R&D. Furthermore, the tax policy appears to stimulate positive technology spillovers. This suggests that R&D tax policies do seem effective in increasing innovation, and not simply devices for relabeling existing spending or shifting innovative activities between firms. The implied elasticities of patenting and R&D with respect to changes in its (tax adjusted) user cost are large. We argue that our R&D elasticities are large compared to existing estimates because we focus on firms that are smaller, which have been to be more likely to be subject to financial constraints, 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 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

[81] Even when we restrict the sample to firms for which the sales criterion binds when using the sales running variable, the proportionate effects are still lower than our baseline results, and the estimates are not statistically significant.

[82] The *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 (Table A15 Panel B). 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 for R&D effect on patents using both criteria as instrumental variables for R&D are similar to our baseline. However, they are less precise due to the inclusion of an additional weak *below-sales-threshold indicator* instrument.

the global financial crisis when credit frictions may have been particularly acute. However, the fact that the impact is also large seven years after the crisis period suggests that the caveats should not be overstated.

We have partially examined equilibrium effects by demonstrating that the R&D tax policy stimulates patenting activity not only for the firms who directly benefited, but also creates spillovers for 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 a higher volume of R&D, especially in the short-run. We believe that this is less likely to be 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; and within the US see 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 should be an important area for future work.

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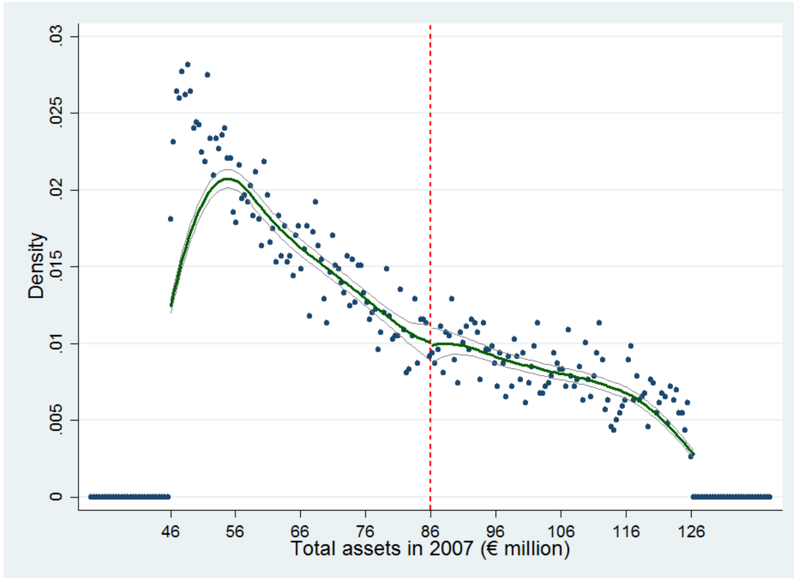
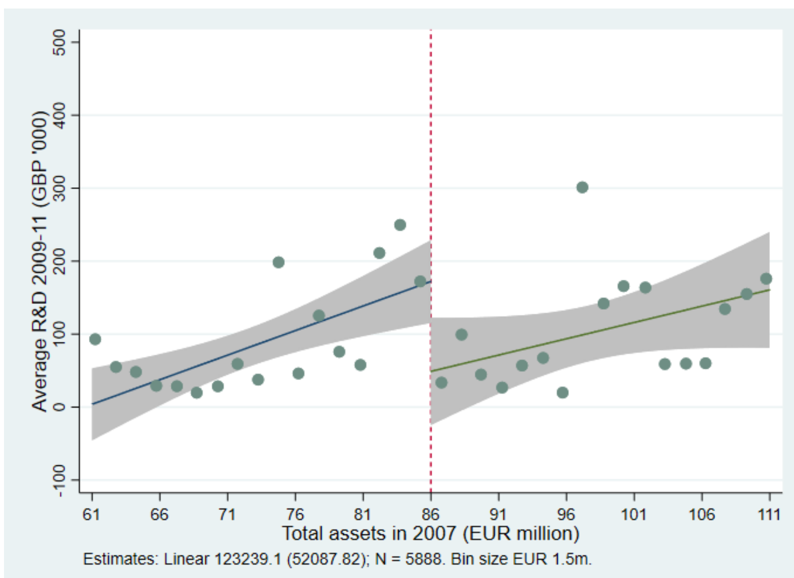
Figure 1. McCrary test for no manipulation at the SME assets threshold in 2007



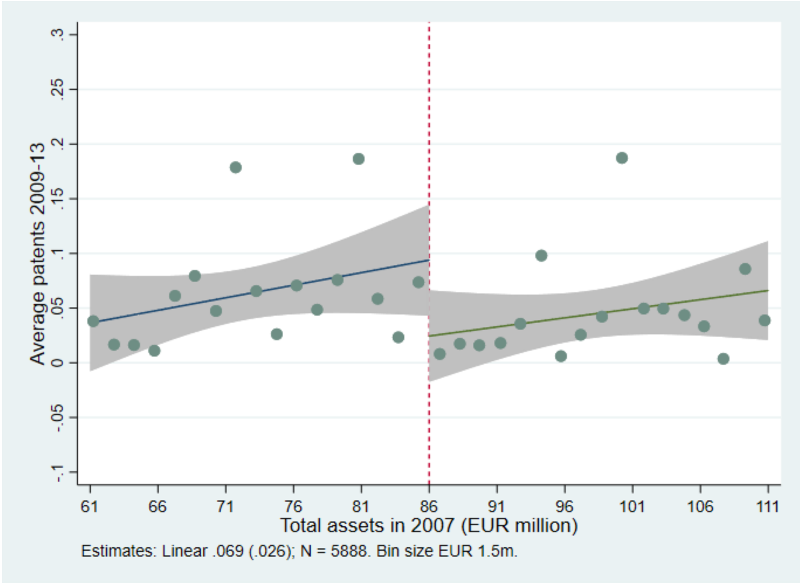
Note: McCrary test for discontinuity in distribution density of total assets in 2007 at the SME assets threshold of €86m. Sample includes firms with total assets in 2007 between €46m and €126m. The discontinuity estimate (log difference in density height at the SME threshold) is -0.026, with standard error of 0.088.

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



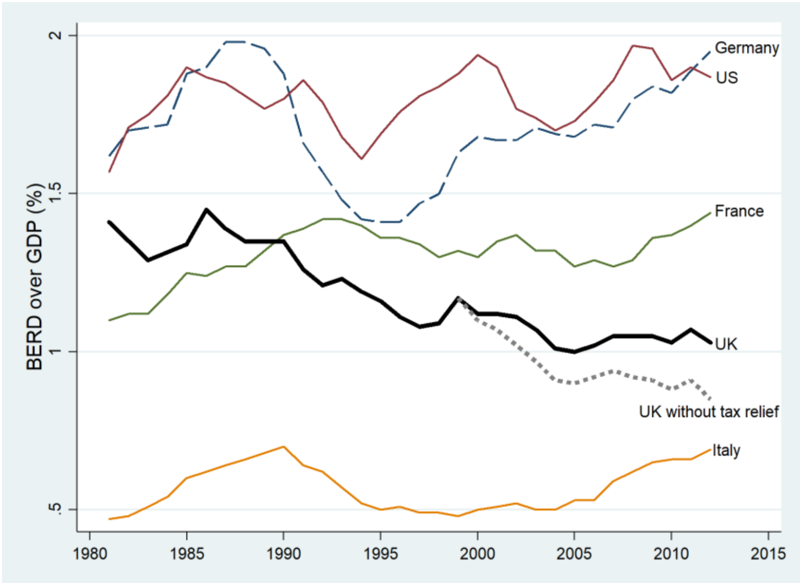
Note: The figure corresponds to the baseline R&D regression based on equation 1, using an OLS Regression Discontinuity (RD) Design. The dependent variable is average R&D expenditure over 2009-11. The running variable is total assets in 2007 with a threshold of €86m. The baseline sample includes firms with total assets in 2007 €25m above and €25m below the cut-off (i.e., between €61m and €111m). Controls for first order polynomials of the running variable separately for each side of the threshold are included. The OLS discontinuity estimate at the €86m threshold is 123.2 with a standard error of 52.0. Each point represents a bin of 184 firms on average, over a 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



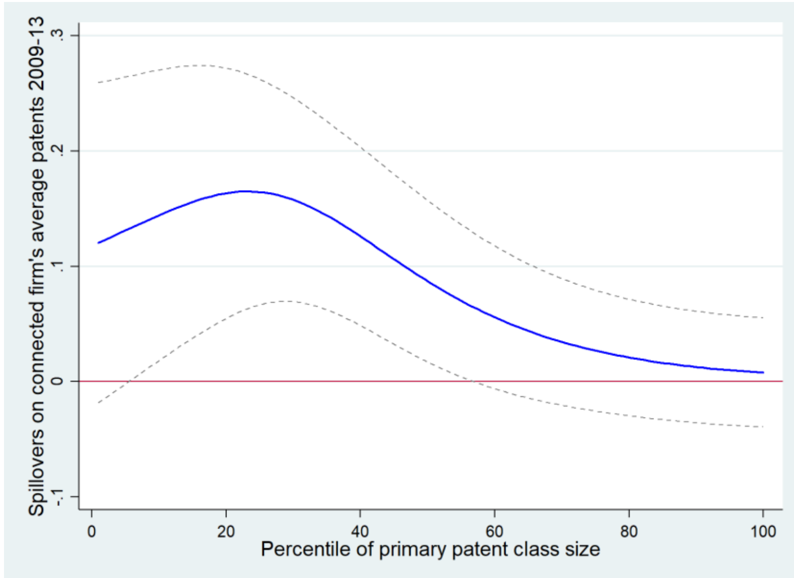
Note: The figure corresponds to the baseline patent regression based on equation (3), using an OLS Regression Discontinuity (RD) Design. The dependent variable is average number of patents over 2009-13. The running variable is total assets in 2007 with a threshold of €86m. Baseline sample includes firms with total assets in 2007 €25m above and below the cut-off (i.e., between €61m and €111m). Controls for first order polynomials of the running variable separately for each side of the threshold are included. The OLS discontinuity estimate at the €86m threshold is 0.069 with a standard error of 0.026. Each point represents a bin of 184 firms on average, over a range of €1.5m. (Bin size is large due to data confidentiality requirement.)

Figure 4. Business Enterprise R&D over GDP, selected countries



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 A.6 for details).

Figure 5. Spillovers on connected firm's patents by primary patent 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 (4), using a Gaussian kernel function of the X-axis variable and a bandwidth of 20% of the range (see Appendix C.1 for details). The 40th percentile of technology class size is 200. The dashed lines indicate the 90% confidence interval for the spillover coefficients.

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. Pre-treatment covariate balance tests and placebo tests

	(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: *** significant at 1% level, ** 5% level, * 10% level. OLS estimates based on the RD Design. The running variable is total assets in 2007 with a threshold of €86m. Baseline sample includes firms with total assets in 2007 within €25m below and above the cut-off (i.e., between €61m and €111m), for whom the corresponding dependent variable is non-missing. Controls for first order polynomials of the running variable separately for each side of the threshold are included. 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.

Table 3. 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: *** significant at 1% level, ** 5% level, * 10% level. OLS estimates based on the RD Design. The running variable is total assets in 2007 with a threshold of €86m. Baseline sample includes firms with total assets in 2007 within €25m below and above the cut-off (i.e., between €61m and €111m). Controls for first order polynomials of the running variable separately for each side of the threshold are included. 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. 2007 real prices.

Table 4: 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: *** significant at 1% level, ** 5% level, * 10% level. OLS estimates based on the RD Design. The running variable is total assets in 2007 with a threshold of €86m. Baseline sample includes firms with total assets in 2007 within €25m below and above the cut-off (i.e., between €61m and €111m). Controls for first order polynomials of the running variable separately for each side of the threshold are included. 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.

Table 5: Effects of R&D tax relief 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
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*
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)
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: *** significant at 1% level, ** 5% level, * 10% level. OLS estimates based on the RD Design. The running variable is total assets in 2007 with a threshold of €86m. Baseline sample includes firms with total assets in 2007 within €25m below and above the cut-off (i.e., between €61m and €111m). Controls for first order polynomials of the running variable separately for each side of the threshold are included. 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 patent 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.

Table 6. Effects of R&D on patents (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: *** significant at 1% level, ** 5% level, * 10% level. Instrumental variable is the indicator whether total assets in 2007 is below €86m. Baseline sample includes firms with total assets in 2007 within €25m below and above the cut-off (i.e., between €61m and €111m). Controls for first order polynomials of the running variable (total assets in 2007) separately for each side of the threshold are included. 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.

Table 7. Heterogeneous effects of R&D tax relief by industry-level proxy for 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: *** significant at 1% level, ** 5% level, * 10% level. OLS estimates based on the RD Design. The running variable is total assets in 2007 with a threshold of €86m. Baseline sample includes firms with total assets in 2007 within €25m below and above the cut-off (i.e., between €61m and €111m). Controls for first order polynomials of the running variable separately for each side of the threshold are included. Robust standard errors are in brackets. Cash/K is calculated as the three-digit 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.

Table 8: R&D knowledge spillovers on patents

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Specification	Reduced form						IV
Dependent variable	**Connected firm's all patent family count (2009-13 average)**						
Sample	Full	Full	Large tech. class	Small tech. class	Small tech. class; additional control	Small tech. class; broad definition	Small tech. class
Baseline firm's below-assets-threshold indicator (in 2007)	0.019	0.067***	0.018	0.196**	0.164*	0.109**	
	(0.012)	(0.019)	(0.011)	(0.093)	(0.086)	(0.049)	
Baseline firm's below-threshold indicator # technology class size *('000)*		-0.029***					
		(0.007)					
Baseline firm's R&D *(£ million)*, 2009-11 average							0.222**
							(0.110)
Difference			0.178* (0.094)				
Anderson-Rubin test p-value							0.036
Dependent variable mean (2006-08)	*0.396*	*0.396*	*0.397*	*0.291*	*0.294*	*0.203*	*0.291*
No. of connected firms	17,632	17,632	16,477	1,190	1,152	2,340	1,190
No. of baseline firms	547	547	487	67	67	78	67
No. of three-digit IPC classes	91	91	55	36	36	36	36
Observations	203,832	203,832	201,739	2,093	2,015	5,708	2,093

Note: *** Significant at 1% level, ** 5% level, * 10% level. Sample of technologically-connected pairs of a baseline firm and a connected firm. Two firms are technologically connected if they (i) patent primarily in the same three-digit technology class, and (ii) have Jaffe technologically proximity of at least 0.75 (except for column 6, in which only (i) applies), computed using all patent applications over 1900-2008. Baseline firms include patenting firms (before 2008) with total assets in 2007 between €61m and €111m. Connected firms include the universe of patenting firms (before 2008). OLS estimates based on the RD Design. The running variable is baseline firm's total assets in 2007 with a threshold of €86m. Controls for (i) first order polynomials of the running variable separately for each side of the threshold and (ii) second order polynomial of connected firm's total assets in 2007 are included. Column 5 additionally controls for connected firm's below-assets-threshold indicator (in 2007). Standard errors in brackets are clustered by baseline firm. 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 significantly different in columns 3 and 4.

Table 9: SME status regressions

	(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: *** significant at 1% level, ** 5% level, * 10% level. OLS estimates based on the RD Design. The running variable is total assets in 2007 with a threshold of €86m. Baseline sample includes firms with total assets in 2007 within €25m below and above the cut-off (i.e., between €61m and €111m). Controls for first order polynomials of the running variable separately for each side of the threshold are included. 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.

APPENDICES: FOR ONLINE PUBLICATION ONLY

Appendix A: Institutional details of policy and tax-adjusted user cost

A.1 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.

Measurements of staff headcount, assets, and sales turnover for ceiling tests: 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.[1] The staff headcount and financial data used for the "ceiling tests" (the maximum values possible for a firm to be eligible for SME status) are those relating to the latest accounting year. Assets and sales are 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). An enterprise passes the ceiling tests if its staff headcount and either its aggregated assets or its aggregated turnover fall below the respective ceilings. An enterprise loses (acquires) its SME status if it fails (passes) the ceiling tests over two consecutive accounting periods.

Account aggregation rules for different enterprise types: In the case of an autonomous enterprise, the staff headcount and financial data are determined exclusively on the basis of the consolidated account of the enterprise itself.[2] 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 linked enterprises' account data are already included through account consolidation.[3]

A.2 UK R&D Tax Relief Scheme

The R&D Tax Scheme includes a SME Scheme and a Large Company ("LCO") component.[4] 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).

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

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[1] 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.

[2] 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.

[3] Linked enterprises are those in which one enterprise is able to exercise control, directly or indirectly, over the affairs of the other.

[4] 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).

income, thus reducing R&D-performing companies' corporate tax liabilities. For example, if a company is allowed an enhancement rate of 75%, for a £10,000 spend on R&D, it can deduct an additional £7,500 from its taxable income before calculating its tax liability. 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.[5] 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.[6]

Qualifying R&D expenditure must be allowable as a deduction in calculating trading profits, which includes all flow costs, employee costs, materials, utilities, software, or subcontracted R&D expenditure (but only if the contractor is an SME).[7] 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. 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.[8] 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.

The evolution of the UK R&D Tax Relief Scheme is summarized in Table A1. It was first introduced in April 2000 only for SMEs (Finance Act 2000), then later extended to large companies starting from April 2002 (Finance Act 2002).[9] 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%.[10]

As discussed in the main paper, 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% (to ensure that state aid intensity stays below the EU imposed limit of 25%). Also from August 2008, the SME Scheme was extended to "larger" SMEs as the

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[5] For 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% x £2000, 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.

[6] 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.

[7] 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.

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

[9] Finance Act 2000 (Chapter 17, Schedule 20) and Finance Act 2002 (Chapter 23, Schedule 12).

[10] 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.

SME ceilings were doubled to 499, €86m, and €100m for staff headcount, 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 other programs. It should also be noted that even though these new SME ceilings were announced in Finance Act 2007, the date on which they became effective (August 1st, 2008) was announced much later, in July 2008.[11]

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.

The formal definition of R&D has been stable over time. To qualify for tax relief the costs must be consistent with the UK accounting definition of R&D under GAAP (accounting standards FRS102 s18, IAS38, FRS105 s13 and SSAP13). "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 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.3 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:

$$\ln G = -\sigma \ln \rho + \sigma \ln U + \ln Z + B \tag{A1}$$

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:

$$lnR = -\sigma \ln \rho + \sigma \ln U + \ln Z + \ln \delta + \mathrm{B} \tag{A2}$$

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

We also consider a knowledge production function:

$$\ln PAT = \mu + \alpha \ln G$$

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

$$lnPAT = -\alpha\sigma \ln \rho + \alpha \ln Z + \alpha\sigma \ln U + \alpha \ln \delta + \alpha\mathrm{B} - \mu$$

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

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

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.

A.4 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):

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

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 $\hat{\lambda}$ 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 $\tilde{\lambda} = \lambda$. Table A7 Panel A 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.[12] This implies that $\tilde{\lambda} \approx \lambda$ in a first-order approximation (as $\frac{(\rho-1)[(1-\lambda_1)(1-\lambda_0)-\lambda_1\lambda_0\rho]}{[1+\lambda_1(\rho-1)][1+\lambda_0(\rho-1)]} \approx 0$).[13]

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) $(1-\lambda_1)(1-\lambda_0) \leq \lambda_1\lambda_0 < \lambda_1\lambda_0\rho$, which implies that the bias is negative. However, when $\lambda_1 + \lambda_o < 1$, the bias could still be either negative or positive.

A.5 Tax-adjusted user cost of R&D

The full formula for tax-adjusted user cost of R&D as described in sub-section 7.2 is:

$$\rho_{t,f} = \left(\Pr(Has\ tax\ liability) \times \frac{\left(1-\tau_t\left(1+e_{t,f}\right)\right)}{(1-\tau_t)} + \Pr(No\ tax\ liability) \times (1-c_{t,f}(1+e_{t,f}))\right) \times (r+\delta)$$

where τ is the effective corporate tax rate, e is the enhancement rate, c is the payable credit rate, r is the real interest rate, δ is the depreciation rate, t denotes year, and f denotes the whether the company is an SME or a large company. Note that $\rho_{t,f}$ varies over time with τ_t, $e_{t,f}$, and $c_{t,f}$.

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, as a result, 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

[12] Formally, the regressions in Table A7 Panel A 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.

[13] 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) $\rho = \frac{(1-\lambda_1)(1-\lambda_0)}{\lambda_1\lambda_0}$.

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).

A.6 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.

A.6.1 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.

<u>SME tax deduction case</u>

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

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

so 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} ($\Delta_{EC} = R_{old} \times 0.82$).

A.6.2 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 (Table A17 Panel B), 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 A17, 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 sub-section 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 Table A17 Panel B. 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 sub-section 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 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 A17 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.

A.6.3 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 4. 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 4. To calculate the counterfactual (the dotted line "UK without tax relief" in Figure 4) we simply deduct the additional qualified R&D that we estimate were created by the R&D tax relief system (second row of Table A17 Panel E) 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.

Appendix B: Data

B.1 CT600 dataset

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.[14] 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.[15]

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.[16] 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).

Our key variables of interest are those related to firms' R&D tax relief claims from CT600's RDTC

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[14] 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 which puts large weight on the biggest R&D performers, we would likely only have a small overlap with firms around the threshold.

[15] 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 A13).

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

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, assets (balance sheet total), sales, and ownership structure.

Table B1 shows that over our study period of 2006-11, we observe claims in 53,491 firm by year 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.[17] However, CT600 sales provides a good measure for firms' growth and performance, given its relatively wide coverage.

B.2 FAME 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.[18]

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 from 2006-11 (covering 3.1 million firms). 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 reported by only 15%, as smaller firms are not required to provide their income statements.[19] The proportion of firms who

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[17] 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.

[18] 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.

[19] 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

report 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 who report sales is 67% and the proportion who report employment is 55%. For this reason, while we do use FAME sales and employment as 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 (UK 4-digit SIC), address, and fixed assets as a proxy for capital stock.

B.3 PATSTAT dataset

Our patent data are drawn from the World Patent Statistical Database (PATSTAT) maintained by the European Patent Office (EPO).[20] 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. PATSTAT data 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.

A patent in country *i* grants a holder an exclusive right to commercially exploit the invention in that country. Accordingly, she will patent her invention in country *i* 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.

In this study, 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 the first year they were filed (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.

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 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.

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simplified balance sheets.

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

[21] 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. 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). A third 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). Fourth, we know whether the patent filed was subsequently granted, with the reasonable presumption that granted patents are of higher value. Fifth, 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.

In PATSTAT, patents are categorized based on the International Patent Classification (IPC). We use IPC codes at three-digit level to construct measures of the technological distance between firms used to investigate spillover effects.

B.4 Sample construction: merging datasets

CT600 was merged 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.[22] 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 and net corporate tax chargeable.[23] 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.[24] For these reasons, we believe sample selection due to incomplete matching between CT600 and FAME is unlikely to be an issue for us.[25]

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.

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[21] 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.

[22] 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).

[23] 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.

[24] 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.

[25] 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.

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 sub-section 4.2.

B.5 Variable construction

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, exactly the same method as used by HMRC.

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 confirmed 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.[26]

We address the presence of outliers in R&D spending or patenting by 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 patenters 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 A3-A5).

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

B.6 Running variable selection: SME criterion binding ratio

We chose total assets as the key running variable as it is the only SME criterion with close to complete coverage in FAME. In addition, as discussed in sub-section 7.6, we also 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 calculate the binding/non-binding ratio for the *assets* criterion as the number of firms with 2007 sales in [€100m, €180m] (i.e., firms for which the assets criterion binds), divided by the number of firms with 2007 sales in [€20m, €100m] (i.e., firms which also meet the sales criterion), conditioned on firms' 2007 total assets being in [€36m, €136m] (i.e., +/-€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] (i.e., firms for which the sales criterion binds), divided by the number of firms with 2007 assets in [€6m, €86m] (i.e., firms which already meet the assets criterion), conditioned on firms' 2007 sales being in [€50m,

[26] 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.

€150m] (i.e., +/-€50m window around the sales threshold of €100m). The binding/non-binding ratio for the assets criterion is 0.36, considerably higher than the same ratio for the sales criterion of 0.20, as visually presented in Figure A8.

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 A14 Panel B. 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 C: R&D technology spillovers

C.1 Semi-parametric estimation of spillovers by primary technology class size

We modify the spillover regression in equation (4) from section 6 to model the potentially heterogeneous effect of baseline firm i's likely-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):

$$PAT_{j,09-13} = \alpha_4(x) + \theta(x)E_{i,2007} + f_4\big(z_{i,2007}, x\big) + g_4\big(z_{j,2007}, x\big) + \varepsilon_{4ij}$$

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.

C.2 Alternative approach to estimating R&D technology spillovers

In this sub-section, we discuss a complementary approach to estimating R&D technology spillovers using a monadic specification instead of the dyadic specification discussed in Section 6. Following the work of Jaffe (1986) we calculate the knowledge spillover pool available to firm $\boldsymbol{j}$ as $\boldsymbol{spilltechR_{j,09-11}} = \sum_{i,i\neq j}\boldsymbol{\omega_{ij}R_{i,09-11}}$ where $\boldsymbol{R_{i,09-11}}$ is the average R&D of firm $\boldsymbol{i}$ over 2009-11 and $\boldsymbol{\omega_{ij}}$ is measure of technological "proximity" between firms $\boldsymbol{i}$ and $\boldsymbol{j}$, computed based on the distribution of technology classes in which the firms patent (e.g., if two firms have identical patent class distributions then proximity is 1; if they patent in entirely different patent classes then proximity is zero).[27] We follow our earlier approach of using $\boldsymbol{E_{i,2007}}$ as instrument for $\boldsymbol{R_{i,09-11}}$ ($\boldsymbol{E_{i,2007}}$ is firm $\boldsymbol{i}$'s below-assets-threshold indicator in 2007).[28] Consequently, we construct $\boldsymbol{spilltechE_{j,09-11}} = \sum_{i,i\neq j}\boldsymbol{\omega_{ij}E_{i,2007}}$ as instrument for $\boldsymbol{spilltechR_{j,09-11}}$. The exclusion restriction requires that the discontinuity-induced random fluctuations in firm $\boldsymbol{i}$*'s* eligibility

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[27] Following Jaffe (1986) we define proximity as the uncentered angular correlation between the vectors of the proportion of patents taken out in each technology class $\omega_{ij} = \frac{F_iF_j'}{(F_iF_i')^{\frac{1}{2}}(F_jF_j')^{\frac{1}{2}}}$. $F_i = (F_{i1}, \dots, F_{i\Upsilon})$ 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. To calculate $F_{i\tau}$, we use information on all patents filed between 1900 and 2011 and their 3-digit International Patent Classification (IPC), which classifies patents into 123 different technology fields. These data are available from PATSTAT. Bloom et al. (2013) show that the Jaffe measure delivers similar results to more sophisticated measures of proximity.

[28] More generally, $E_{i,2007} = I\{\, z_{i,2007} \leq \tilde{z}\,\}$ is a binary indicator equal to one if the 2007 financial variable $z_{i,2007}$ is equal to or less than the corresponding new SME threshold for it, $\tilde{z}$.

would only affect technologically-connected firm $\boldsymbol{j}$'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 $\boldsymbol{j}$, $\boldsymbol{spilltechR_{j,09-11}}$, on firm $\boldsymbol{j}$'s innovation, $\boldsymbol{PAT_{j,09-13}}$, controlling for firm $\boldsymbol{j}$'s own R&D using $\boldsymbol{E_{j,2007}}$ as an instrument:

$$PAT_{j,09-13} = \alpha + \psi spilltechR_{j,09-11} + F_j(Z_{2007}) + \zeta E_{j,2007} + g\left(z_{j,2007}\right) + \pi techconnect_j + \varepsilon_j$$

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 $techconnect_j = \sum_{i,i\neq j}\omega_{ij}$.[29] We instrument $spilltechR_{j,09-11}$ with $spilltechE_{j,2007}$. $F_j(Z_{2007})$ and $g(z_{j,2007})$ are polynomial controls for $spilltechE_{j,2007}$ 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 above equation 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.[30] 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 $spilltechE_{j,2007}$ significantly predicts $spilltechR_{j,09-11}$ (column (1)) and the instrument $E_{j,2007}$ significantly predicts connected firm j's own R&D (column (2)). The instruments $spilltechSME_{j,2007}$ 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, $spilltechE_{j,2007}$, 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, $spilltechR_{j,09-11}$ *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)

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[29] Given equation (1) for firm i's R&D as $R_{i,09-11} = \alpha + \beta^R E_{i,2007} + f\left(z_{i,2007}\right) + \varepsilon_i$, aggregating across all firm i's around the SME asset threshold and using ω_{ij} as weights gives:

$$\sum_{i,i\neq j}\omega_{ij}R_{i,09-11} = \alpha\sum_{i,i\neq j}\omega_{ij} + \beta^R\sum_{i,i\neq j}\omega_{ij}E_{i,2007} + \sum_{i,i\neq j}\omega_{ij}f\left(z_{i,2007}\right) + \sum_{i,i\neq j}\omega_{ij}\varepsilon_i$$
$$\Rightarrow spilltechR_{j,09-11} = \alpha techconnect_j + \beta^R spilltechE_{j,2007} + F_j(Z_{2007}) + \nu_j$$

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

[30] Note that $spilltechR_{j,09-11}$ is calculated using the population of all possible firm i's, while $spilltechE_{j,2007}$ 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 $spilltechE_{j,2007}$ 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.

including $R_{j,09-11}$ as a control and using $E_{j,2007}$ as the corresponding instrument (column (6)). The latter is a very demanding specification, and even though the corresponding spillover coefficient is no longer significant,[31] 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.[32]

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 $spilltechE_{j,2007}$ 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 et al., 2013), (iv) reconstructing the standard Jaffe measure of technological proximity using only information on patents filed up to 2008, and (v) using smaller or large sample to calculate the instrument $spilltechE_{j,2007}$ 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 et al. (2013) and construct $spillsicR_{j,09-11} = \sum_{i,i\neq j} \phi_{ij} R_{i,09-11}$ 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.[33] We also construct $spillsicE_{j,2007} = \sum_{i,i\neq j} \phi_{ij} E_{j,2007}$ as instrument for $spillsicR_{j,09-11}$. We found no significant effects of $spillsicR_{j,09-11}$ 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.

[31] If we use robust standard errors instead of bootstrapped standard errors, the estimated coefficient (standard error) for $spilltechR_{j,09-11}$ from column (6)'s specification is 0.014 (0.007), statistically significant at 5% level.

[32] 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 $\widehat{\psi}\,\overline{techconnect_i} = 0.014 \times 44 = 0.616$.

[33] $\phi_{ij} = 1$ 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 3-digit Standard Industry Classification (SIC). These data are available from FAME.

Table A1. Design of UK R&D Tax Relief Scheme, 2000-2012

Effective from		SME ceilings: Employ-ment	SME ceilings: Total assets	SME ceilings: Turn-over	Enhancement rate: SME	Enhancement rate: Large company	Payable credit rate: SME	Payable credit rate: 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%	"	Large companies: 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 ("ceiling tests"). The measurements and account aggregation rules for employment, total assets, and sales are set according to 1996/280/EC (up to December 31st, 2004) and 2003/361/EC (from January 1st, 2005). 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.

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

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	SME			**Large company**			**Arc % difference user cost**	**Log difference user cost**
Tax relief scheme	Deduction	Payable credit	Average	Deduction	Payable credit	Average		
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 sub-section 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. Main R&D and patent results among firms below and above employment threshold

Panel A. Firms with 2007 employment below 500

	(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 of at least 500

	(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: *** significant at 1% level, ** 5% level, * 10% level. OLS estimates based on the RD Design. The running variable is total assets in 2007 with a threshold of €86m. Subsamples of baseline sample that includes firms with total assets in 2007 within €25m below and above the cut-off (i.e., between €61m and €111m). Controls for first order polynomials of the running variable separately for each side of the threshold are included. Robust standard errors are in brackets. **Panel A:** Subsample of firms with 2007 employment below the new SME threshold of 500. **Panel B:** Subsample of firms with 2007 employment at or above the new SME threshold of 500. Firms with missing 2007 employment are not included in either subsamples.

Table A4. Robustness checks for R&D regressions

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	2nd	3rd	1st	1st	1st	1st	2nd	2nd	1st	1st
Kernel weight			Epa	Tri					Tri	Tri
Sample assets (€m)	61-111	61-111	61-111	61-111	71-101	66-106	56-116	51-121	56-116	51-121
Firms	5,888	5,888	5,888	5,888	3,394	4,615	7,255	8,818	7,255	8,818

Panel B.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Dependent variable	**R&D expenditure, 2009-11 average *(£ '000)***								
Specification	Industry & location fixed effects			Alternative LDV	Alternative winsorization parameter			Poisson	Negative binomial
Below-assets-threshold in 2007	106.9*	121.7**	103.6**	60.8*	156.9**	87.3**	43.5*	1.31***	1.22**
	(57.2)	(52.0)	(52.2)	(33.9)	(64.6)	(38.6)	(25.0)	(0.49)	(0.49)
Fixed effects	Industry	Location	Ind. x Loc.						
Year of LDV				2007					
Winsorized window	2.5%	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	5,888	5,872	5,888	5,888

Note: *** significant at 1% level, ** 5% level, * 10% level. OLS estimates based on the RD Design. The running variable is total assets in 2007 with a threshold of €86m. Baseline sample includes firms in 2007 within €25m below and above the cut-off (i.e., between €61m and €111m). Controls for first order polynomials of running variable separately for each side of the threshold are included. 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 (1)-(3) add industry (4-digit SIC), location (2-digit postcode), and industry x location (2-digit SIC x 1-digit postcode) fixed effects. Column (4) adds R&D expenditure in 2007 as lagged dependent variable control. Columns (5)-(7) use samples with different winsorization parameter or sample excluding outliers in R&D expenditure. Column (8) and (9) uses Poisson and negative binomial specifications instead of OLS, to allow for a proportionate effect on R&D (as in a semi-log specification).

Table A5. Robustness checks for patent regressions

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	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
Sample assets (€m)	61-111	61-111	61-111	61-111	71-101	66-106	56-116	51-121	56-116	51-121
Firms	5,888	5,888	5,888	5,888	3,394	4,615	7,255	8,818	7,255	8,818

Panel B.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Dependent variable	**All patent family count, 2009-13 average**								
Specification	Industry & location fixed effects			Alternative LDV	Alternative winsorization Parameter			Poisson	Negative binomial
Below-assets-threshold in 2007	0.063*	0.065***	0.061**	0.047**	0.067**	0.063***	0.070***	1.29***	1.46***
	(0.034)	(0.025)	(0.024)	(0.022)	(0.027)	(0.024)	(0.026)	(0.46)	(0.47)
Fixed effects	Industry	Location	Ind. x Loc.						
Year of LDV				2007					
Winsorized window	2.5%	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	5,888	5,872	5,888	5,888

Note: *** significant at 1% level, ** 5% level, * 10% level. OLS estimates based on the RD Design. The running variable is total assets in 2007 with a threshold of €86m. Baseline sample includes firms in 2007 within €25m below and above the cut-off (i.e., between €61m and €111m). Controls for first order polynomials of running variable separately for each side of the threshold are included. 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 (1)-(3) add industry (4-digit SIC), location (2-digit postcode), and industry x location (2-digit SIC x 1-digit postcode) fixed effects. Column (4) adds all patent family count in 2007 as lagged dependent variable control. Columns (5)-(7) use samples with different winsorization parameter or sample excluding outliers in all patent family count. Column (8) and (9) uses Poisson and negative binomial specifications instead of OLS, to allow for a proportionate effect on patents (as in a semi-log specification).

Table A6. Robustness checks for effects of R&D on patents (IV regressions)

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 *(£m)*, 2009-11 avg.	0.345	0.301	0.475**	0.449**	0.370	0.428*	0.278	0.489**	0.558**	0.655*
	(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)	61-111	61-111	61-111	61-111	71-101	66-106	56-116	51-121	56-116	51-121
Firms	5,888	5,888	5,888	5,888	3,394	4,615	7,255	8,818	7,255	8,818

Panel B.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Dependent variable	**All patent family count, 2009-13 average**							
Specification	Industry & location fixed effects			LDV control		Alternative winsorization parameter		
R&D expenditure *(£m)*, 2009-11 avg.	0.587	0.534*	0.589	0.434*	0.421*	0.428*	0.721**	1.597*
	(0.435)	(0.304)	(0.411)	(0.243)	(0.251)	(0.224)	(0.355)	(0.939)
Fixed effects	Industry	Location	Ind. x Loc.					
Year of LDV				2006-08 average	2007			
Winsorized window	2.5%	2.5%	2.5%	2.5%	2.5%	1.0%	5.0%	No outliers
Firms	4,504	5,868	4,498	5,888	5,888	5,888	5,888	5,872

Note: *** significant at 1% level, ** 5% level, * 10% level. IV estimates based on the (fuzzy) RD Design. Instrumental variable is the indicator whether total assets in 2007 is below €86m. Baseline sample includes firms with total assets in 2007 within €25m below and above the cut-off (i.e., between €61m and €111m). Controls for first order polynomials of the running variable (total assets in 2007) separately for each side of the threshold are included. 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 (1)-(3) add industry (4-digit SIC), location (2-digit postcode), and industry x location (2-digit SIC x 1-digit postcode) fixed effects. Columns (4) and (5) add average all patent family count over 2006-2008 or all patent family count in 2007 as lagged dependent variable control. Columns (6)-(8) use samples with different winsorization parameter or sample excluding outliers in all patent family count.

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: *** significant at 1% level, ** 5% level, * 10% level. OLS estimates based on the RD Design. The running variable is total assets in 2007 with a threshold of €86m. Baseline sample includes firms with total assets in 2007 within €25m below and above the cut-off (i.e., between €61m and €111m). Controls for first order polynomials of the running variable separately for each side of the threshold are included. 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 4-digit 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.

Table A8. Discontinuities in 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 (0.011)	0.006 (0.012)	0.013 (0.011)	0.011* (0.007)	0.008 (0.007)	0.014* (0.007)	0.013** (0.006)	0.018*** (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: *** significant at 1% level, ** 5% level, * 10% level. OLS estimates based on the RD Design. The running variable is total assets in 2007 with a threshold of €86m. Baseline sample includes firms with total assets in 2007 within €25m below and above the cut-off (i.e., between €61m and €111m). Controls for first order polynomials of running variable separately for each side of the threshold are included. 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.

Table A9. 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 expendi-ture (*£ '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* (885)	6.3 (9.6)	1.50** (0.68)	0.002 (0.005)	1.40** (0.63)	-0.000 (0.002)	1.80** (0.91)	0.007 (0.005)	1.89*** (0.66)	-0.002 (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* (879)		1.50** (0.67)		1.40** (0.62)		1.79** (0.90)		1.89*** (0.65)	
Firms	259	5,629	172	5,716	117	5,771	152	5,736	106	5,782

Note: *** significant at 1% level, ** 5% level, * 10% level. OLS estimates based on the RD Design. The running variable is total assets in 2007 with a threshold of €86m. Baseline sample includes firms with total assets in 2007 within €25m below and above the cut-off (i.e., between €61m and €111m). Controls for first order polynomials of running variable separately for each side of the threshold are included. Robust standard errors are in brackets. Past period is the pre-policy period of 2006-2008.

Table A10. 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. 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: *** significant at 1% level, ** 5% level, * 10% level. Robust standard errors are in brackets. Industry patenting intensity is calculated as the share of firms in the 4-digit 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 based on the RD Design. The running variable is total assets in 2007 with a threshold of €86m. Baseline sample includes firms with total assets in 2007 within €25m below and above the cut-off (i.e., between €61m and €111m). Controls for first order polynomials of running variable separately for each side of the threshold are included. **Panel B:** IV estimates based on the (fuzzy) RD Design. Instrumental variable is the indicator whether total assets in 2007 is below €86m. Baseline sample includes firms with total assets in 2007 within €25m below and above the cut-off (i.e., between €61m and €111m). Controls for first order polynomial of RDD running variable (total assets in 2007) separately for each side of the threshold are included.

Table A11. Heterogeneous effects of R&D tax relief by Biotech and Pharmaceutical (BTP) and Information and Communication Technology (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: *** significant at 1% level, ** 5% level, * 10% level. Robust standard errors are in brackets. OLS estimates based on the RD Design. The running variable is total assets in 2007 with a threshold of €86m. Baseline sample includes firms with total assets in 2007 within €25m below and above the cut-off (i.e., between €61m and €111m). Controls for first order polynomials of running variable separately for each side of the threshold are included. **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 3-digit industries in total number of BTP patent applications over 2006-2011. **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 3-digit industries in total number of ICT patent applications over 2006-2011.

Table A12. Heterogeneous effects of R&D tax relief by firms' 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. 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: *** significant at 1% level, ** 5% level, * 10% level. Robust standard errors are in brackets. Past capital investments is calculated as average machinery and plant investments over 2005-2007 reported in CT600 (as coverage of capital expenditure in FAME is limited). **Panel A:** OLS estimates based on the RD Design. The running variable is total assets in 2007 with a threshold of €86m. Baseline sample includes firms with total assets in 2007 within €25m below and above the cut-off (i.e., between €61m and €111m). Controls for first order polynomials of running variable separately for each side of the threshold are included. **Panel B:** IV estimates based on the RD Design. Instrumental variable is the indicator whether total assets in 2007 is below €86m. Baseline sample includes firms with total assets in 2007 within €25m below and above the cut-off (i.e., between €61m and €111m). Controls for first order polynomial of RDD running variable (total assets in 2007) separately for each side of the threshold are included.

Table A13: Effects of R&D tax relief on other 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: *** significant at 1% level, ** 5% level, * 10% level. OLS estimates based on the RD Design. The running variable is total assets in 2007 with a threshold of €86m. Controls for first order polynomials of running variable separately for each side of the threshold are included. Robust standard errors are in brackets. Columns (1)-(5) employ the full baseline sample for firms with total assets in 2007 within €25m below and above the cut-off (i.e., between €61m and €111m). Columns (6)-(10) use the subsample of R&D performing firms during 2009-2011 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 (1) and (6)). 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).

Table A14. Effects of R&D tax relief on other measures of firms 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: *** significant at 1% level, ** 5% level, * 10% level. OLS estimates based on the RD Design. The running variable is total assets in 2007 with a threshold of €86m. Baseline sample includes firms with total assets in 2007 within €25m below and above the cut-off (i.e., between €61m and €111m). Controls for first order polynomials of the running variable separately for each side of the threshold and 2-digit industry dummies are included. 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 calculated as $\ln(value\ added) - \propto_k \ln(capital) - \propto_l \ln(wages)$, in which value added sales minus imputed materials and $\propto_k$ and $\propto_l$ are estimated using Olley-Pakes production function estimation separately for each 2-digit industry across all firms in the FAME dataset over the 2000-2005 period. 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)).

Table A15. 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: *** significant at 1% level, ** 5% level, * 10% level. Robust standard errors are in brackets. **Panel A:** OLS estimates based on the RD Design. The running variable in columns (1) and (2) is total assets in 2007 with threshold of €86m. The running variable in columns (3) and (6) is sales in 2007 with threshold of €100m. The running variable in columns (7) and (8) is employment in 2007 with threshold of 499. Controls for first order polynomials of running variable separately for each side of the threshold are included. **Panel B:** OLS estimates based on the RD Design for R&D and patent regressions (columns 1-2 and 4-5). IV estimates based on the (fuzzy) RD Design where the instrumental variable is the indicator whether total assets in 2007 is below €86m (columns 3 and 6). The running variables are total assets in 2007 with threshold of €86m and sales in 2007 with threshold of €100m. Instrumental variable in columns (3) and (6) are the indicator whether total assets in 2007 is below €86m and the indicator whether sales in 2007 is below €100m. Controls for first order polynomials of the running variables (total assets in 2007 and sales in 2007) separately for each side of the respective threshold are included. 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.

Table A16. 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 sub-section 7.2 and the note to Table A16 Panel A. Log-difference-elasticity approach in row (2) is explained in detail in the note to Table A16 Panel B. 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 2009-2011 (row 2) and SME status over 2008-2009 (row 3). These estimates are reported in Table 2 columns (4) and (6) respectively. Row (5) uses the discontinuity estimates with lagged dependent variable control from Table 3 column (10) (for R&D) and column (7) of Table 5 Panel B (for patents). Row (6) uses average R&D and patents over 2006-2007 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 weights. Relevant estimates are reported in Tables A3-5. 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 A.5). Differences between each approach and the baseline case in row (1) are highlighted in bold (for input estimates only).

Table A17. Bootstrapping elasticity estimates

Panel A.

	(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 sub-section 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 Table 3 column (5) and its empirical distribution. Column (2) corresponds to Table 4 column (9); column (4) – R&D pre-policy baseline mean; column (6) – Table 6 Panel B column (6); 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 Table A2 column (7)). 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.

	(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 Table 3 column (5) and its empirical distribution. Column (2) corresponds to Table 4 column (9); column (4) – R&D pre-policy baseline mean; column (6) – Table 6 Panel B column (6); 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 Table A2 column (8)). 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 A18. 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 A.6 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 sub-section 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 A19. 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: *** significant at 1% level, ** 5% level, * 10% level. OLS estimates based on the RD Design. The running variable is total assets in 2007 with a threshold of €86m. Baseline sample includes firms with total assets in 2007 within €25m below and above the cut-off (i.e. between €61m and €111m). Controls for first order polynomials of the running variable separately for each side of the threshold are included. 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 3-digit industry level using UK firm data over 2000-2005 (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 include 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).

Table A20. 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: *** Significant at 1% level, ** 5% level, * 10% level. 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.

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

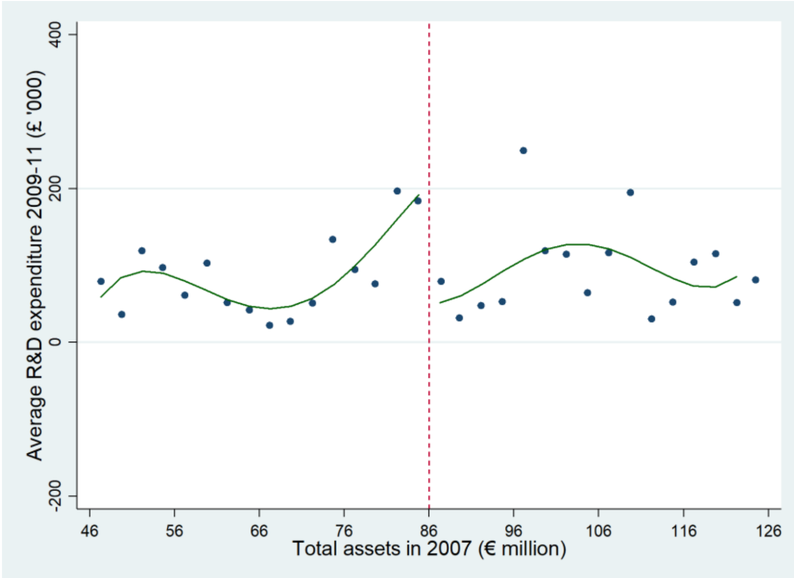
	Unit	2006	2007	2008	2009	2010	2011	2006-2011
No. firms	*Firm*	1,780,531	1,858,209	1,870,089	1,898,721	1,973,722	2,073,930	3,140,060
Variable coverage								
No. firms with total assets	*Firm*	1,732,169	1,807,743	1,818,448	1,843,896	1,914,848	2,015,058	3,012,397
Total assets coverage	*%*	97.3%	97.3%	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%

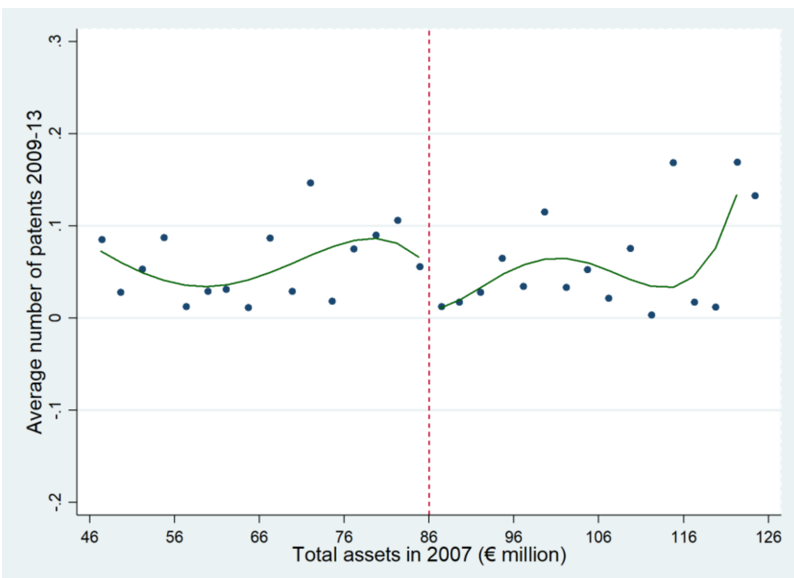
Note: Average qualifying R&D expenditure and estimated Exchequer costs are computed for firms with R&D tax relief claims in the corresponding year or period. Average patents, EPO patents, and UK patents are computed for firms with corresponding patent applications in corresponding year or period.

Figure A1. Discontinuity in average R&D expenditure over 2009-2011



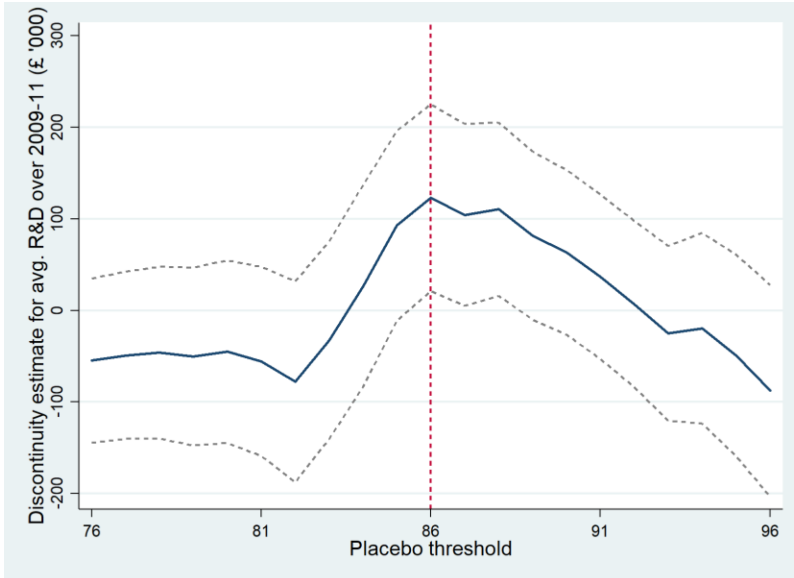
Note: The figure corresponds to CCT RD Design R&D regression. The dependent variable is average R&D expenditure over 2009-2011. The running variable is total assets in 2007 with a threshold of €86m. Controls for fourth order polynomials of the running variable separately on each side of the threshold are included. The CCT discontinuity estimate at the €86m threshold is 160.0 with a standard error of 64.2. Bin size for the scatter plot is €2.5m.

Figure A2. Discontinuities in average number of patents over 2009-2013



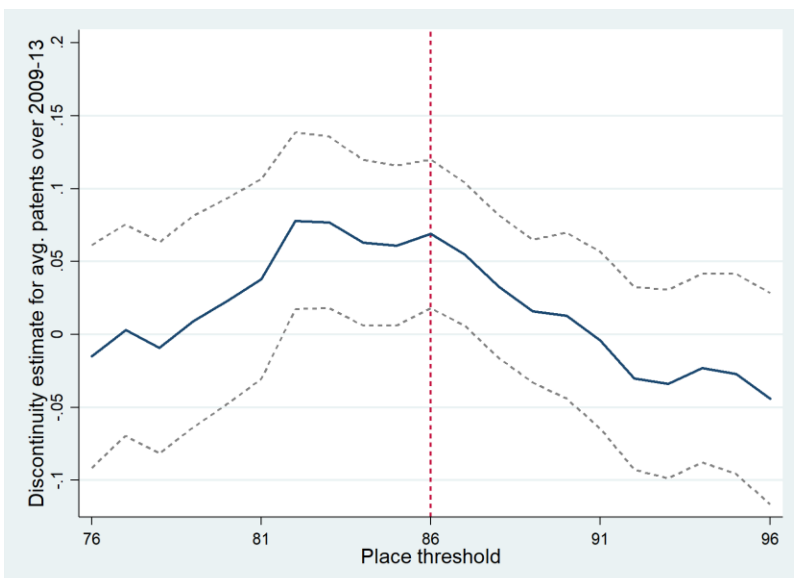
Note: The figure corresponds to CCT RD Design patent regression. The dependent variable is average number of patents over 2009-2013. The running variable is total assets in 2007 with a threshold of €86m. Controls for fourth order polynomials of the running variable separately on each side of the threshold are included. The CCT discontinuity estimate at the €86m threshold is 0.065 with a standard error of 0.023. Bin size for the scatter plot is €2.5m.

Figure A3. Discontinuities in average R&D over 2009-2011 at "pseudo" SME assets thresholds



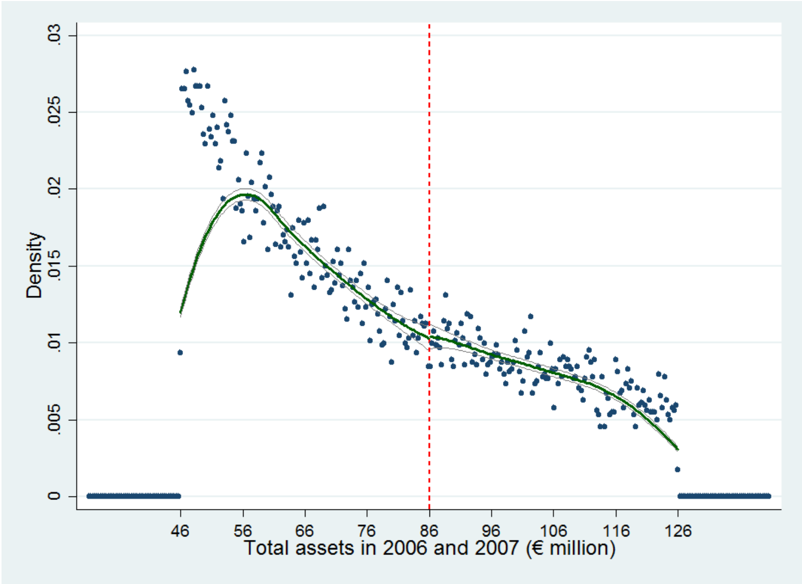
Note: This figure presents the R&D discontinuity estimates as a function of placebo threshold. The coefficient at each threshold is estimated using the baseline R&D regression based on equation (1) (OLS RD Design with average R&D expenditure over 2009-2011 as the dependent variable). The running variable is total assets in 2007. Baseline sample includes firms with total assets in 2007 €25m above and below the corresponding placebo threshold. Controls for first order polynomials of running variable separately for each side of the placebo threshold are included. The dashed lines indicate the 95% confidence interval for the discontinuity estimates.

Figure A4. Discontinuities in average number of patents over 2009-2013 at "pseudo" SME assets thresholds



Note: This figure presents the patent discontinuity estimates as a function of placebo threshold. The coefficient at each threshold is estimated using the baseline patent regression based on equation (3) (OLS RD Design with average number of patents over 2009-2013 as the dependent variable). The running variable is total assets in 2007. Baseline sample includes firms with total assets in 2007 €25m above and below the corresponding placebo threshold. Controls for first order polynomials of running variable separately for each side of the placebo threshold are included. The dashed lines indicate the 95% confidence interval for the discontinuity estimates.

Figure A5. McCrary test for no manipulation at the SME assets threshold before the policy change

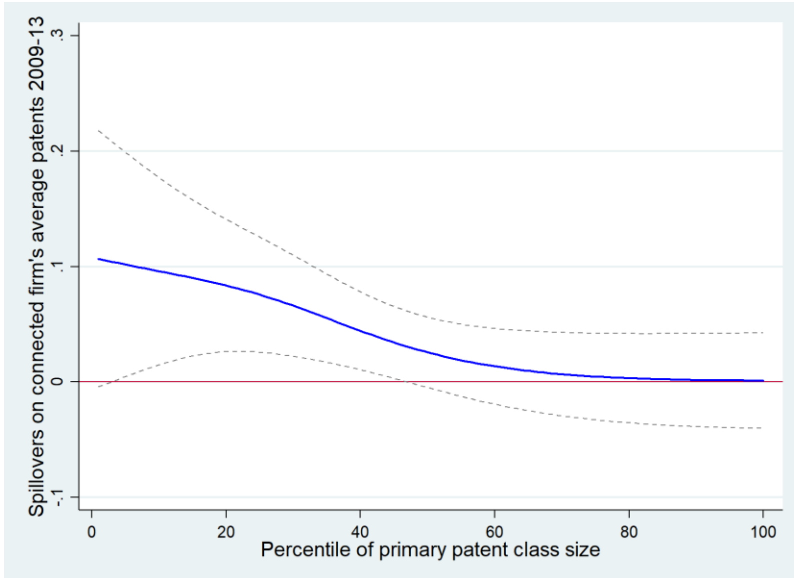


Note: McCrary test for discontinuity in distribution density of total assets at the SME assets threshold of €86m before the policy change, pooling together total assets in 2006 and 2007. Sample includes firms with total assets in [€46m, €126m] in each of the year. The discontinuity estimate (log difference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

Figure A6. McCrary test for no manipulation at the SME assets threshold after the policy change

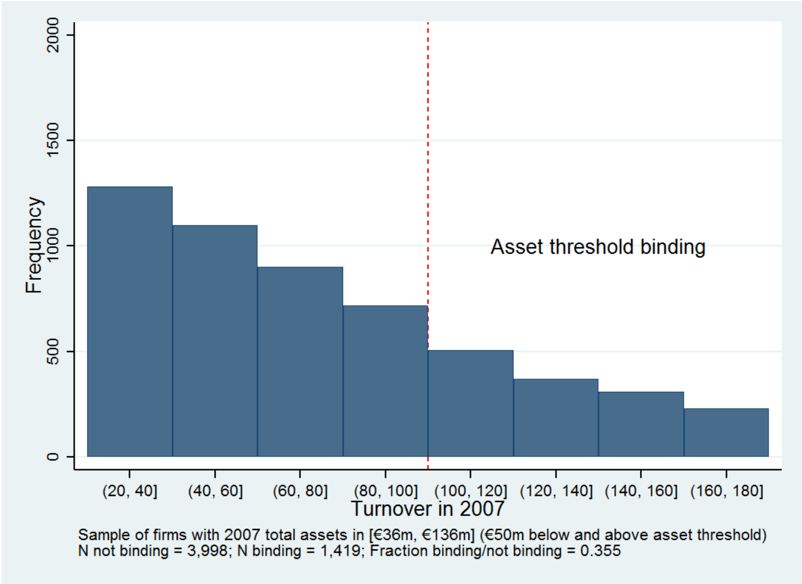
Note: McCrary test for discontinuity in distribution density of total assets at the SME assets threshold of €86m after the policy change, pooling together total assets in 2009, 2010, and 2011. Sample includes firms with total assets in [€46m, €126m] in each of the year. The discontinuity estimate (log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

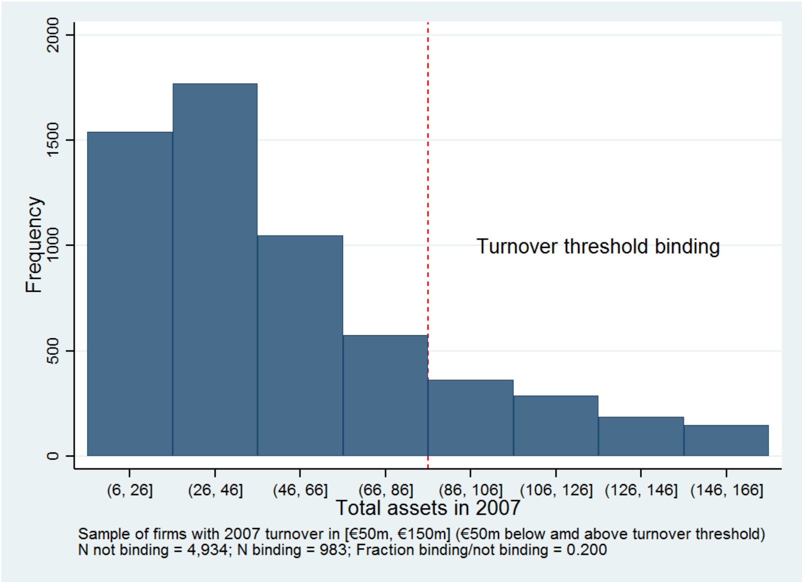
<u>Figure A7. Spillovers on “loosely” connected firm’s patents by primary patent class size</u>



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 3-digit technology class. The semiparametric estimation is based on equation (4), using a Gaussian kernel function of the X-axis variable and a bandwidth of 20% of the range (see Appendix C.1 for details). The 40th percentile of technology class size is 200. The dashed lines indicate the 90% confidence interval for the spillover coefficients.

Figure A8. Number of firms with binding and not-binding assets and revenue thresholds





Note: Assets threshold is not binding for firms with 2007 sales in (€20m, €100m] and binding for firms with 2007 sales in (€100m, €180m]. Sales threshold is not binding for firms with 2007 total assets in (€6m, €86m] and binding for firms with 2007 total assets in (€86m, €166m].