Tax Incentives, R&D and Productivity

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Abstract

This thesis explores the causal relationships between tax incentives, research and development (R&D) and productivity. Using R&D survey data from the United Kingdom (UK) Office for National Statistics and administrative data on corporation tax returns from HM Revenue and Customs, I first conduct empirical analyses of tax incentive policies for R&D, and then estimate the elasticity of output with respect to firms' own R&D efforts as well as external R&D performed by neighboring firms in technology and product space. In the first two chapters which focus on tax incentive policies and their evaluation, I am able to identify the policy effect of interest by exploiting two significant reforms in the UK in 2002 and 2008. I find that tax incentives had a positive and significant stimulating effect on businesses' R&D spending. I argue that the availability of a quasi-experimental set up helps in better identifying the policy impact. The production function estimation exercise in the third chapter shows that double counting of R&D human resources and materials in the production function causes the elasticity of output with respect to the firms' own R&D to be substantially underestimated. I also find that the R&D done in multi-unit enterprise groups is productive for the production facilities which themselves do not perform R&D. The Jaffe (1986) and Bloom et al. (2013) measures of external R&D, which account for closeness of firms in technology and product space can be constructed and included in the production function in the spirit of Griliches (1979). I find that the point estimate for the elasticity of output with respect to firms' own R&D is around 3 percent and statistically significant. Evidence is mixed regarding the productivity effects of R&D carried out by competitors in the product market or neighboring firms in technology space. The detailed data sets used in this study offer valuable resources for empirical work on R&D and productivity.

Disclaimer

WORD COUNT
The body of this thesis consists of 157 pages with a typical page (page 4) containing 404 words. Therefore, the thesis is 63,428 words long (including references, equations, graphs and tables).

SOFTWARE
This thesis was typed using TeXworks for LaTeX, which was also used to create all tables. Stata13 was used as the statistical package. Microsoft Excel was used to generate remaining figures.

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The views expressed in this thesis are my own and any errors and omissions are my sole responsibility.

Irem Guceri

Introduction and Motivation

Productivity differences are persistent and pronounced, and policymakers around the world have embraced the idea of adopting ambitious research and development (R&D) and innovation programs with the aim of giving a boost to productivity and growth. Since 2000, the United Kingdom (UK) has been expanding its support to R&D activity by businesses, acknowledging that its R&D and productivity performance has consistently been weaker than many developed countries in the recent decades. Business R&D intensity, measured by total business R&D as a share of its value added remained below those of the United States (US), Japan, France and Germany, which may be considered comparators for the UK. The UK private sector spent around 1.1 percent of its total value added on R&D in 2012, while this ratio was around 2 percent for the US and for Germany[1].

An ambitious R&D and innovation policy agenda is justifiable in economic theory. The decentralized market equilibrium level of private R&D falls short of the social optimum (Jones and Williams (1998)), which is an idea that has its roots in the seminal work of Arrow (1962). The private sector underinvests in R&D partly because R&D spillovers prevent firms from reaping all the proceeds from their R&D efforts and partly because the firms are unable to fully insure against the risks involved in inventive activity.

Empirical work on the effectiveness of R&D policy and the productivity of R&D faces both data and estimation-related challenges. Micro data on R&D is scarce, and usually available only for larger firms. Investment in R&D, which is treated analogously to investment in physical capital in the literature[2], is a combination of the R&D labor

[1]Source: OECD Main Science and Technology Indicators
[2]This train of thought follows Griliches (1979).

force - composed of scientists, engineers and R&D support staff -, supplies and R&D capital goods. This generates measurement issues because R&D labor, materials and capital are also measured as part of ordinary inputs unless the breakdown of these inputs into their components of R&D, production and other activities is available in the data. Other measurement challenges are related to the conversion of R&D flow into a 'knowledge stock' variable, the choice of appropriate R&D deflators, determining the lag structure, and quantifying spillovers (Hall et al. (2009)). Identification challenges arise from simultaneity and reverse causality concerns.

In this thesis, I explore the causal relationships between tax policy, R&D and productivity using micro level data on R&D in the private sector. Chapter 1 and Chapter 2 focus on the impact of tax policy on R&D spending and present quasi-experimental evaluations of tax incentive policies in the UK, exploiting the variation in the tax price of R&D thanks to two significant reforms in 2002 and 2008. This policy set up, which features two major discontinuities (for which suitable data is available), offers a unique opportunity for identifying the impact of tax policy on private R&D using quasi-experimental designs. Chapter 3 then examines the contribution of R&D to micro level productivity, considering R&D that is both internal and external to the firm. In Chapter 3, I investigate the productivity impact of three different layers of R&D activity on UK manufacturing firms. The first is the effect of R&D carried out in an R&D-performing unit's own productivity. The second is the productivity effect on a production unit of R&D performed by the other members of a multi-unit group. The third is the R&D external to the group, which in this context, refers to the R&D performed by neighboring firms in the technology and product market space. I use detailed information on both the sectors of R&D and the sectors of manufacturing activity from official R&D and production surveys, which make it possible to address some of the measurement issues that arise in estimating the elasticity of output with respect to firms' own and external R&D.

In order to increase private spending on R&D, governments have started to rely heavily on fiscal incentives. The UK's 2011 Budget Document introduced the much debated 'Patent Box' policy, which grants a 'reduced 10 percent rate of corporate tax for profits arising from patents, effective from April 2013'[3]. In the same document, the Government proposed an enhancement to the small and medium enterprise (SME) tax incentives. The SME scheme started in 2000 with a rate of relief amounting to 150 percent of eligible expenses. In 2008, the SME definition was expanded to include a group of larger firms, and the 150 percent deduction rate was raised to 175 percent, followed by further increases to 200 percent in 2011 and to 225 percent in 2012. The large company scheme has been in place since 2002. A prominent question now is whether the impact is high enough for these enhanced tax incentives to generate the desired level of R&D expenditures by the private sector.

With these policy considerations in mind, Chapter 1 of this thesis exploits the differential change in the user cost of R&D after the introduction of the R&D Tax Relief for Large Companies. When the policy was introduced in 2002, SMEs were already benefiting from the R&D Tax Relief for SMEs, which had been introduced at an earlier date. Therefore, enterprises that were just below the SME size threshold in 2002, and hence had been eligible for the SME scheme, constitute a natural control group, while the slightly larger enterprises that only started benefiting from the scheme in 2002 are allocated to the treatment group in the analysis. As the review of the literature on tax incentives for R&D by Hall and Van Reenen (2000) highlights: "A long-standing problem in the investment literature is the intractability of finding exogenous variation in the user cost of capital (p.450)". The quasi-experimental set up in this paper offers such exogenous variation and distinguishes the paper from others in the literature. The policy discontinuity allows for the use of a difference-in-differences methodology for identification. Using this methodology, in Chapter 1, I find that the treated firms increased their R&D spending differentially by about 18 percent after the introduction of the policy, implying a user cost elasticity estimate around -1.4.

Both Chapter 1 and Chapter 3 benefit from micro data provided by the Office for National Statistics (ONS). In Chapter 1, the ONS data set Business Enterprise Research and Development Survey (BERD) is matched with the Business Structure Database (business register), providing information on employment, turnover and own-

[3]Treasury (2011); p.56, Article 2.71

ership structures for all UK enterprises as well as R&D.

Chapter 2, which is co-authored with Li Liu, builds on the R&D tax incentive policy set up introduced in Chapter 1, this time exploiting a later policy change which radically reduced the user cost of R&D capital for companies which have between 250-500 employees. The 2008 reform studied in Chapter 2 doubled the employment, turnover and asset thresholds for defining an SME in the context of eligibility to the more generous SME scheme, reducing the user cost of R&D capital for these companies by up to 29 percent. The availability of administrative panel data from the HM Revenue and Customs (HMRC) on the universe of corporate taxpayers in the UK makes it possible to move from the 'intent to treat' approach of Chapter 1 to actual treatment in Chapter 2, and exploit the panel dimension of the data set in addressing the intensive margin question about the effectiveness of R&D tax incentives. We are also able to observe a set of tax-related variables and control for possible effects of the tax position. To our knowledge, the corporation tax returns data set is being used for the first time in the R&D context. We find that the companies whose status changed from 'large' to 'SME' roughly doubled their R&D intensity for spending that qualifies for R&D tax incentives, increasing this ratio on average by about 12 percentage points in response to the policy change. This finding is robust to benchmarking against different control groups composed of slightly larger and slightly smaller companies than the treated ones.

Chapter 3 connects R&D with productivity and presents estimates of the elasticity of output with respect to the R&D input. If R&D is productive, or a certain type of R&D is found to be more productive than others, then it may be desirable to adjust the policy framework to encourage such activities. The data used in Chapter 3 provides sufficiently disaggregated information at the micro level to quantify the downward bias in the elasticity estimates due to the mismeasurement (double counting) of labor and materials. I find that a substantial portion of the contribution of firms' own R&D to productivity is overlooked when the double counting correction is not possible. The point estimates for the reporting units' own R&D elasticity increase from 0.6 percent to 2-3 percent after the correction. For the production units that do not carry out

R&D themselves, the elasticity of output with respect to the R&D performed by the other members of the group is estimated to be 0.6 percent and significant. Regarding the elasticities with respect to R&D that is external to the firm, I find mixed results depending on the particular measure of external R&D that is used.

Motivated by the global trends in ambitious private R&D and productivity policies and the availability of micro level data from the UK, the three papers that constitute the first, second and third chapters of this thesis present individual empirical analyses that endeavor to pinpoint the causal relationships between tax policy, R&D and productivity. Each of the chapters has a similar structure, beginning with an introduction, followed by a background or methodology section, which also presents a review of the literature (Chapter 3 presents empirical evidence in the literature in a separate chapter). Each of the chapters has a dedicated data section which describes the data sets merged and used in these studies and presents summary statistics. The data sections are followed by the empirical analysis, results and robustness checks. There are separate concluding sections in each of the chapters, and Chapter 4 concludes the thesis with an overall discussion of the findings and future work that emerges from the three chapters. References are listed separately at the end of each chapter.

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Chapter 1

Tax incentives and R&D: an evaluation of the 2002 UK reform using micro data

Abstract

The United Kingdom introduced an R&D tax incentive scheme first for SMEs in 2000 and then for large firms in 2002, gradually increasing the generosity of both schemes after 2008. This study exploits the differences between companies with similar characteristics that were just above the size threshold for eligibility to the SME scheme and those that were just below, before and after the 2002 reform. This allows for a difference-in-differences approach to measure the (additional) impact of the tax incentives on firms around this size threshold. Treatment group firms are found to have increased their R&D spending by around 18 percent on average in response to the large company tax incentive, implying a user cost elasticity of -1.35. We do not find significant differences in this effect between sectors.

JEL Classification: H25, O31, O38

Keywords: R&D, tax credits, difference-in-differences

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Contents

1 Introduction

Private returns to knowledge production have been shown to fall short of its social returns in the pioneering work of Arrow (1962). Inappropriability of innovation outputs and technology spillovers reduce the private sector's incentives to engage in the socially optimal level of innovative activity. Due to the public good nature of research and development (R&D) investments, governments have been actively supporting R&D performed by businesses.

This paper uses a difference-in-differences approach to investigate the effects of tax incentives for R&D, using the micro level Business Enterprise Research and Development (BERD) data for the UK. A clear cut discontinuity in the design of the schemes is exploited in order to identify the policy impact. A difference-in-differences approach has been possible thanks to the step by step implementation of the tax incentive scheme in the UK. Medium sized firms in the treatment group have been found to increase R&D spending by about 18 percent, indicating an implied user cost elasticity of around -1.35. The tax incentives are found to have prevented a downward trend in R&D spending. Despite this paper's focus on the UK case, the implications are general for tax incentives and R&D policy.

Medium sized firms are an important engine for innovative activity. Measuring SMEs' contribution to R&D is difficult, as reporting of formal R&D in published accounts is only compulsory for larger corporations. However, the entrepreneurship and innovation literature documents the role played by SMEs in aggregate innovative activity, emphasizing the importance of small businesses in the forward leap of the United States (US) in innovation towards the end of the twentieth century (Acs and Audretsch (1993)). The data used in this study enables that the effect of an R&D tax incentive on medium sized firms be identified.

The UK scheme is particularly suitable for the difference-in-differences design to analyze medium sized firms, thanks to the timing differences in the introduction of tax incentives first for SMEs and then for large companies. This allows the examination of the effect on firms that were marginally above the size threshold for eligibility to the SME scheme, as they started benefiting from R&D tax incentives only in 2002, exactly two years after the introduction of the SME tax incentive scheme. Firms that were marginally below the size threshold for eligibility to the SME scheme then constitute the control group for this study. The treatment and control groups are limited to medium sized companies to maintain comparability between the two groups.

In most policy implementations, the announcement of the scheme before implementation may cause changes in the behavior of affected agents. With investment tax breaks, it can be expected that firms may delay their investment spending for a few periods until the introduction of the policy to attain the maximum possible benefit from the pre-announced incentive schemes. In the estimation stage, this paper explores the possibility of firms delaying their R&D spending strategically to increase the benefit from the policy.

The next section presents some aggregate trends in the R&D performance of UK businesses, followed by a summary of relevant events that took place in the run up to the introduction of R&D tax breaks and a description of the tax incentive schemes in the UK. It then outlines the theoretical background, while reviewing the existing literature on evaluating R&D tax incentive schemes. The third section describes the data, the fourth section presents the estimation procedure and robustness checks and the final section concludes.

2 Background

2.1 Trends in the R&D intensity of the UK private sector

The OECD Frascati Manual (OECD (2002)) sets out clear guidelines for defining research, development, R&D personnel, R&D capital goods, facilities, and other related terminology. The main expenditure items for R&D activities are:

- Current expenditures: labor, materials, supplies and 'other';

- Capital expenditures: land, buildings, instruments, equipment and software.

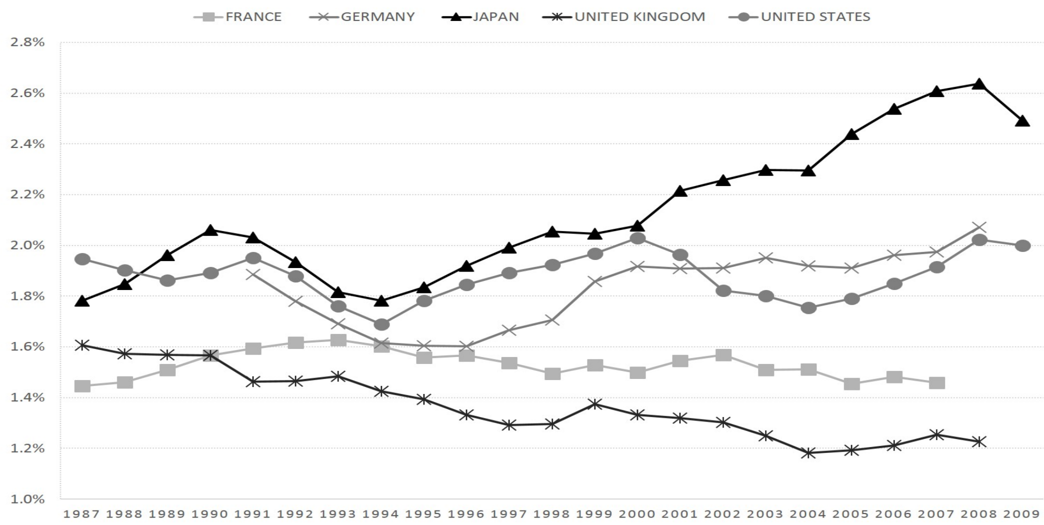
The main sectors which fund R&D activities are: (i) business enterprise[1], (ii) government, (iii) private non-profit, (iv) higher education, (v) abroad. Having obtained the funding from these sources, public or private sector institutions then 'perform' R&D. Therefore, 'funding' and 'performance' of R&D need not take place under one roof. The main focus here is the business enterprise sector expenditures on research and development (BERD), which corresponds to the R&D performed by the private sector.

R&D intensity measures the ratio of R&D expenditures to an output measure, which can be the gross domestic product in the macro context. In the past several decades, the UK private sector's R&D investment performance has been sluggish both in absolute terms and in terms of BERD intensity with respect to comparators such as the United States, Germany, France and Japan.

The OECD Structural Analysis (STAN) and Analytical Business Enterprise Research and Development (ANBERD) Databases report cross country time series data on R&D expenditure volumes and provide a sectoral breakdown. Using these figures, cross country comparisons of R&D intensities can be obtained, as in Figure 1. Figure 1 shows that total BERD as a share of value added has been lower in the UK than in Japan, Germany, France and the USA over the period 1990-2008. Earlier

[1] In the Frascati Manual, 'Business enterprise' is defined as 'all firms, organizations and institutions whose primary activity is the market production of goods or services (other than higher education) for sale to the general public at an economically significant price' and 'the private non-profit institutions mainly serving them (p.54)'. For the private non-profit institutions, their allocation to the business enterprise sector as opposed to the private non-profit sector depends on how they are administered and financed. The decision mechanism for such institutions can be found in the Frascati Manual (p.55).

Figure 1: Total BERD intensity, UK and comparators



Source: OECD

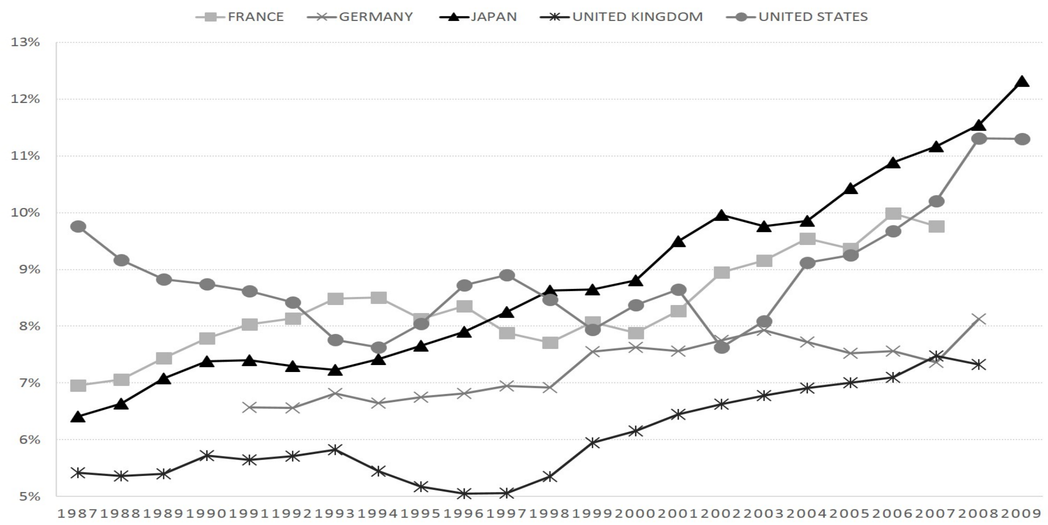
studies (see, for instance, Van Reenen (1997), Griffith and Harrison (2003)) have shown that this relative decline of UK BERD intensity has been continuing for several decades. At this aggregate level without controlling for any other factors, the introduction of tax credits for R&D spending in the UK in 2000 and 2002 appears to have had little impact.

Despite the poor relative performance in overall BERD intensity, the UK manufacturing sector BERD as a share of manufacturing sector value added, in contrast, has shown a steady increase and a tendency toward catching up with its peers. This is illustrated in Figure 2, which shows that the UK manufacturing sector BERD intensity has been rising over the most recent decade for which this data is available and since the UK R&D tax credits were introduced. In 2000s, as the UK manufacturing sector BERD intensity experienced a rise, so did its competitors'; France, Japan and the US all experienced steep rises, with only Germany demonstrating a rather horizontal trend. In an earlier paper, we noted that these peer trends in neighboring countries may have been a significant factor in driving the rise in the UK manufacturing sector R&D intensity, but even controlling for these effects, the UK experienced a steeper rise starting around the time of introduction of the R&D tax incentives (Bond and Guceri (2012)).

In general, BERD performed by the services sector as a share of this sector's value added is much lower than that of manufacturing. The share of manufacturing sectors in total UK value added dropped from 26 percent in 1980 to 13 percent in 2007, while the share of service sectors has risen from 56 percent to 76 percent. It is therefore reasonable to argue that the compositional shift in the UK economy towards service sectors is among the primary reasons for the declining overall BERD intensity in the UK.

Within manufacturing sub-sectors, there are large heterogeneities in trends of R&D intensity,

Figure 2: Manufacturing sector BERD intensity, UK and comparators



Source: OECD

which can be observed in Figure 3 for broad technology groups[2]. The UK high technology sectors have experienced a steep rise in R&D intensity starting in 1997, while R&D intensity in medium technology sectors did not demonstrate similar trends over the same period. If we magnify the neighborhood of medium high and medium low technology sectors, as in the right hand side panel of Figure 3, it can be observed that the increasing trend starting in late 1990s is much more mild for these sectors, with small drops in R&D intensity in some of the years. It is therefore fair to argue that the increasing trend in the UK manufacturing sector R&D intensity was driven mostly by the high technology sectors.

From the point of view of the neoclassical theory of investment, there does not seem to be an obvious reason for different sectors to be affected differently by the implementation of a tax incentive scheme for R&D. In Section 2.3, I discuss these theoretical underpinnings and in the empirical analysis, conduct checks to examine whether there is significant sectoral heterogeneity in firms' response to the R&D tax incentives at the micro level.

Higher technology sub-sectors of manufacturing have been growing both in their total R&D spending and also in terms of value added (Figure 4). While the total value added and R&D intensity of higher technology industries have been increasing, the number of such enterprises and their total employment have been falling[3]. Such reallocation within manufacturing towards higher technology

[2]A technology classification is available by the OECD, where the groups are identified as high technology, medium high technology, medium low technology and low technology sectors. The latest version of the classification is explained in the OECD Science, Technology and Innovation Scoreboard for 2003 and it is based on three indicators for technology and R&D intensity, averaged over ten large OECD countries.

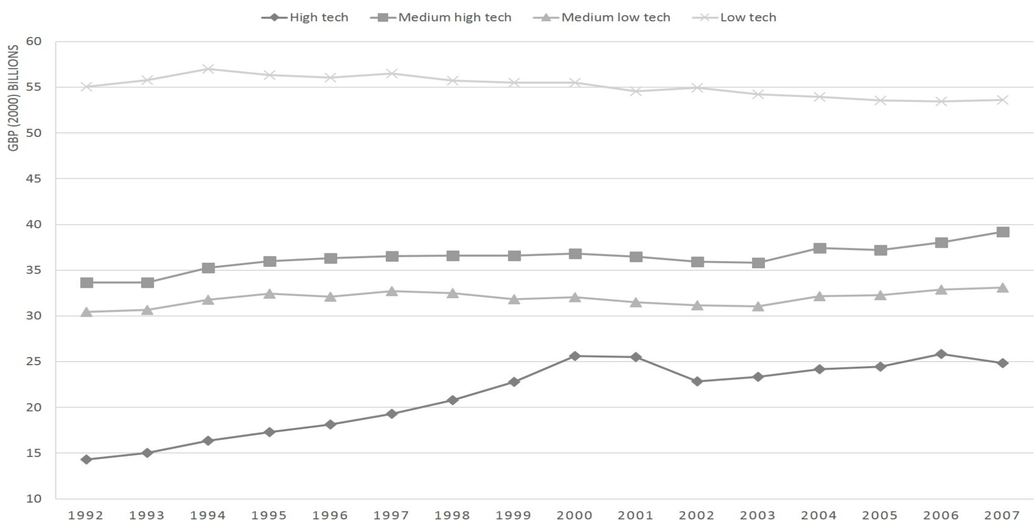
[3]Source: OECD and Business Structure Database over 1998-2007 made available through the Secure Data Service.

Figure 3: BERD intensity of technology groups

Source: OECD

sub-sectors is commonly observed in developed economies. One explanation for this shift is discussed in the empirical trade literature, which finds that import competition drives productivity higher in lower technology import-competing sectors while moving the focus of local manufacturing towards more high technology sectors. Such movements may explain the steeper rise in R&D intensity of UK manufacturing after 1997 (See, among others, Pavcnik (2002) and Bloom et al. (2011)).

Figure 4: Total value added in constant (2000) prices by manufacturing sub-sectors



Source: OECD

2.2 The UK R&D tax incentive scheme in early 2000s

The term 'R&D tax credit' is often used to refer to the general class of fiscal incentives which allow a special treatment of R&D expenditure for tax purposes, encompassing a range of tax incentives for both current and capital expenditures: tax credits, cash credits, enhanced deductions, special depreciation allowance terms, enhanced loss carrybacks and carryforwards, to list a few. The treatment of R&D expenditure is different for economic, accounting and tax purposes. From an economic perspective, R&D is a type of investment; its main objective is to generate higher revenues in the future. From an accounting perspective, on the other hand, the majority of R&D is treated as current expenditure and such expenditure is 100 percent deducted against current revenue in the calculation of profits each period. If there are no special tax incentives, the tax treatment is broadly in line with the accounting treatment and most of the spending on R&D is expensed in the computation of taxable income. For the small part of R&D that is capitalized, firms can only deduct from their accounting profits some estimate of the depreciation charge on the stock of R&D capital in each period. Currently in the UK, as in many other countries, both the current and the capital expenditures on R&D are subject to a special tax treatment, and the details of this is explained in the rest of this section.

Tax incentive schemes for R&D can be of two types: (i) incremental, where firms benefit only to the extent that they exceed some base level of R&D that they have previously been performing[4] and (ii) volume-based, where firms enjoy benefits on all their R&D expenditure, regardless of their past level. It is becoming more and more common to introduce or increase the emphasis on volume-based schemes among industrialized countries, as these are simpler and can reach a larger group of beneficiaries.

The UK R&D Tax Relief for Corporation Tax is relatively generous in the sense that both the SME and the large company schemes are volume-based. The schemes are in the form of enhanced deductions of qualifying current expenditures from taxable income. France had an incremental tax credit until 2008, and then switched to a volume-based credit, greatly simplifying the design of the preceding policy. The US provides an incremental tax credit with a 20-year carryforward option, which is a longer time period than that allowed in most countries. Canada provides a volume-based credit, and both Canada and the US also provide sub-national tax credits (See, for instance, Wilson (2009) for a discussion of sub-national tax credits).

Discussions on a more favorable tax treatment of R&D in the UK began in the late 1990s and more detailed consultations followed in the subsequent years. This was at least partly in response to the declining trend in the R&D intensity of the UK economy overall, which was already at levels below those of comparators such as France, Japan and Germany as demonstrated in Figure 1. Before 2000, when the first significant tax breaks were introduced, all of current expenditure on R&D was

[4]Countries apply different rules regarding the base R&D expenditure that the firm needs to exceed.

100 percent deductible against taxable income and a subset of capital expenditures could be expensed under the Research and Development Allowance[5].

The UK R&D Tax Relief for Corporation Tax was introduced in two stages. First, the SME scheme was implemented in April 2000 and then later in 2002, the large company scheme was introduced. The SME scheme was a combination of an enhanced deduction and cash credits, with the former applying to companies with positive taxable profits and the latter to those companies which incurred a tax loss in the reference period. The SME scheme applied to companies which satisfied the SME definition of the EC Regulation 1996/280/EC and allowed these firms to deduct, for every £100 of qualifying R&D expenditure, £150 from their taxable income[6]. These companies could claim up to 24 percent of their R&D expenditure in cash if they did not have taxable profit. The large company scheme was, in a sense, less generous: it allowed the companies that were above the SME threshold to deduct, for every £100 expenditure, £125 against taxable income and did not grant any cash credits. When a SME conducts subcontracted R&D as a result of a contractual relationship with a large company, then the R&D undertaken by the SME is also subjected to the deduction rates for large companies.

The enhanced deduction rates increased from 1 April 2008 onwards, and this was followed by a change in the thresholds for defining an 'SME' for tax credit purposes[7]. The firm size thresholds before the policy change are shown in Figure 5. These changes were announced in the 2006 Budget. To reduce the risk of capturing changes to R&D following from this announcement, the empirical analysis in this study uses data up to and including calendar year 2006 but not later.

According to the EU regulations, the SME definition consists of size thresholds and also requirements related to owner-subsidiary relationships[8]. This implies that small firms which are subsidiaries of large companies, which own stakes over and above 25 percent in the firm, cannot benefit from the SME incentive scheme. To qualify for the SME credit, companies need to satisfy the employment criterion and then either the balance sheet size or the turnover criteria. Figure 5 depicts the relevant size thresholds which define an SME in terms of pre-2008 criteria, which is the period relevant for this study.

During the period of interest for this study, eligibility for the SME tax incentive required that the company has fewer than 250 employees, and either a balance sheet size of less than €27 million (€43 million from 2005) or turnover less than €40 million (€50 million from 2005). In addition to having satisfied these criteria, the company should not have been owned by a group that exceeds these limits, or the individual subsidiaries, when aggregated, should not have exceeded these thresholds. Ownership

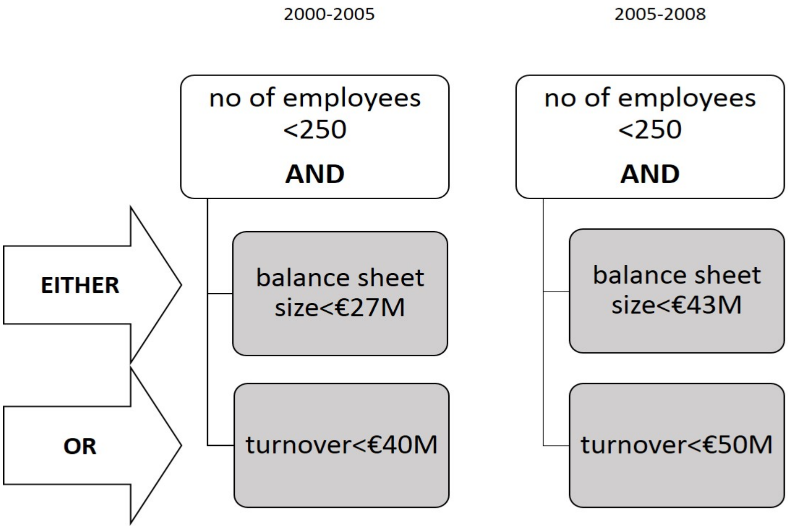
[5]Formerly known as the 'Scientific Research Allowance'. These capital allowances are still available.

[6]SME definitions are explained in detail later.

[7]The size definition change took place on 1 August 2008, in line with the Corporation Tax Act (CTA09/Ss1119 - 1121). Further detail is provided in Chapter 2 of this thesis.

[8]The criteria for eligibility to the SME tax incentive scheme was determined based on the relevant EC Regulation. Depending on the year, these were: 1996/280/EC and 2003/361/EC, with the latter taking effect for accounting periods ending later than 1 January 2005.

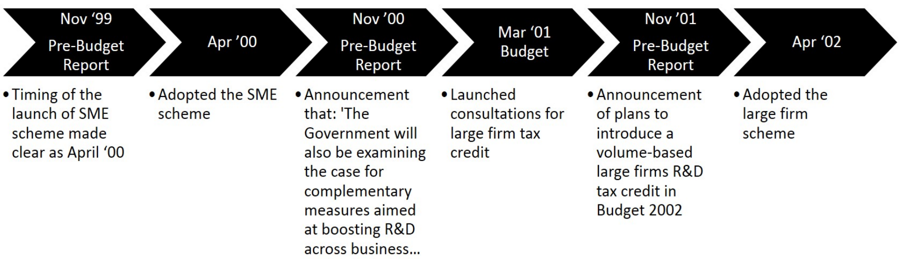
Figure 5: Size thresholds for SME tax credit, early years



in this context refers to more than 25 percent of the capital or voting rights.

Earlier in the paper, I alluded to the possibility that companies may anticipate the introduction of the tax credit and hence behave strategically by delaying their expenditures on R&D until after the implementation of the policy. Such strategic behavior might have been likely in the case of the R&D Tax Relief, as the policy was announced well before its introduction, both for the SME scheme and the large company scheme. Figure 6 presents the major events in relation to the implementation of the R&D Tax Relief, where it can be seen that the government announced its plans to introduce R&D tax breaks in 1998, without giving much detail about the rates, conditions or their timeline. March 2001 marked the beginning of consultations for a large company tax credit, and the announcement of its introduction followed in November 2001. We will later show that despite the early announcement, there is little evidence that larger firms delayed their R&D spending until after the policy implementation.

Figure 6: Events in the early years of the R&D Tax Relief



2.3 An overview of the theoretical underpinnings

The theoretical background on evaluating R&D tax credit schemes is influenced by the literature on tax incentives for physical investment, which is based on the user cost of capital as a determinant of investment decisions, first formalized by Jorgenson (1963) and then developed by Hall and Jorgenson (1967). In their seminal paper, Hall and Jorgenson devise a model of investment to analyze the effect of the investment tax credits and various forms of depreciation allowances in the United States. Their model is based on Jorgenson's 'Theory of Investment Behavior (1963),' building on the neoclassical optimal capital accumulation framework in which firms maximize their profits subject to a form of neoclassical production function by choosing input levels. For simplicity, the model assumes that replacement investment is made at a rate proportional to the capital stock and the investment is not irreversible. Under these assumptions, firms then set their demand for capital input at the level where the marginal product of capital is equal to the 'user cost of capital'. The user cost is described as: "the shadow price or implicit rental of one unit of capital service per period of time (Jorgenson (1963; p.249))". Hall and Jorgenson embed taxation, depreciation allowances and tax credit rates into the present discounted value from 'capital services', equate this to the price of capital goods and find an optimal level of capital for the firm as a function of output price, output quantity, user cost of capital and the elasticity of output with respect to capital. Both their theoretical finding and the empirical analysis point to a significant positive impact of tax credits and depreciation allowance schemes on the firm's capital intensity.

Following Griliches (1979), 'R&D capital stock' or 'knowledge stock' can be considered analogously to the stock of physical capital. The main difference lies in the empirical result, as dynamic models often find longer adjustment periods in the context of R&D investment, which may be due to for instance training requirements for staff upon acquisition of new computer software, setting up advancements in equipment and adaptation of newly hired R&D personnel.

Summarizing this theoretical framework in simplified terms helps in demonstrating the relationship between tax incentives and R&D. Firms acquire knowledge stock (R&D capital) to maximize profits subject to the law of motion of R&D capital. The first order condition equates the marginal product of (R&D) capital to its user cost and the marginal product of the variable input to its real price. Assuming a Cobb Douglas production function, the cost of knowledge capital is then inversely related to the optimal level of (R&D) capital[9]:

$$C^* = \alpha \frac{Q}{U} \tag{1}$$

where Q is the output level, α is the elasticity of output with respect to knowledge stock and U is the

[9]See Jorgenson et al. (1965), Jorgenson (1963) and Hall and Jorgenson (1967) for a formal discussion. The results generalize to other constant elasticity of substitution (CES) production functions.

user cost of capital[10]. Taking logs and rearranging:

$$lnC - lnQ = constant - lnU \tag{2}$$

The user cost of knowledge capital must equal the before tax present value of a unit of investment in R&D so that the marginal project breaks even. A standard expression for the user cost of R&D capital can be derived as in Bloom et al. (1997):

$$U = \frac{1-A}{1-\tau}[r+\delta] \tag{3}$$

where τ is the statutory tax rate and r is the discount rate. A represents the net present value of all current and future depreciation allowances and tax credits applicable to the marginal R&D investment, so they are reductions in the cost of making a unit investment in R&D. The form of A depends on the design of the tax incentive system. When there is 100 percent expensing of R&D expenditure and no special tax credits, $A = \tau$, offsetting the effect of corporate income tax on the required rate of return. With an additional tax credit or an enhanced deduction for more than 100 percent of the R&D expenditure, $A > \tau$, leading to a lower required rate of return.

Tax incentives therefore enter the R&D equation through the user cost term. The user cost, scaled by the firm size, is directly related to the R&D investment undertaken by the firm.

This paper is influenced by the simple neoclassical model of optimal R&D presented here as a motivation for tax incentives to affect the accumulation of knowledge capital in the firm; however, there may be other channels through which tax incentives may affect R&D spending. The quasi-experimental research design used in this study is not reliant on any particular theoretical model, but the discussion in Section 4.3 on our implied user cost elasticity estimates relate to the framework summarized in this section.

2.4 Estimates of the impact of R&D tax credits

The review by Hall and Van Reenen (2000) underlines the importance of finding exogenous variation in the user cost of capital to identify the effect of tax incentive-type R&D support policies. This is not only a challenge in the R&D literature, but also it features heavily in the literature that examines the relationship between tax policy and physical investment.

To date, a clear policy discontinuity as in the UK R&D Tax Relief schemes has not been exploited

[10] In order to increase R&D capital as a share of total output, firms increase R&D investment as a share of output. For our empirical specification, the relationship between R&D investment and R&D capital need not be proportional, but for the purposes of the model summarized in this section, under a steady state assumption, C can be shown to equal $\frac{\kappa+1}{\kappa+\delta}R_{it}$ with κ denoting the growth rate of the capital stock, δ denoting the rate of depreciation of R&D capital and R_{it} denoting R&D investment.

in other papers in this literature. Our study identifies the policy impact by focusing on the variation at the size threshold for eligibility to the SME scheme. Through this policy experiment, we can back out an estimate for the user cost elasticity, given that the drop in the user cost of R&D capital in the UK induced by the introduction of the large company R&D Tax Relief was about 13 percent (Bond and Guceri (2012)).

Bloom et al. (2002) employ the Hall-Jorgenson (1967) approach to calculate the tax-adjusted cost of investing in R&D across a panel of nine OECD countries over nineteen years. Specifying a dynamic model with manufacturing sector business enterprise R&D intensity as the dependent variable, they find a negative long run elasticity with respect to the user cost of R&D, with a value close to minus one.

In their paper, Bond and Guceri (2012) use publicly available macro level data to first calculate the reduction in the user cost of R&D induced by the scheme, then compare the evolution of manufacturing sector BERD intensity with predictions based on the model estimated by Bloom et al. (2002). They find that the increase in R&D in response to the introduction of the tax credit has been around 13 percent, in line with the Bloom et al. prediction, but with quicker adjustment to the long run equilibrium.

An evaluation of the Dutch R&D tax incentive scheme is carried out by Lokshin and Mohnen (2012), who work with an unbalanced panel data set covering the period 1996-2004. They assume a CES production function (as conventional in the literature) and a constant price elasticity of demand. They present three different empirical models to estimate the user cost elasticity of R&D stock: (i) a static model with no adjustment dynamics, (ii) a partial adjustment model (following Nadiri and Rosen (1969)), (iii) an error correction model. Their findings, which are consistent across the models, point to a significant negative long run elasticity of R&D stock with respect to its user cost in the range 0.54-0.79 in absolute value, with a relatively fast convergence of about 2-3 years. Mairesse and Mulkay (2011) study the R&D tax incentive scheme in France, which has gradually moved from an incremental scheme over the period 2004-2008, to a fully volume based scheme in 2008, increasing the budgetary cost of the program threefold. Their study has two components: the first component analyzes the effect of the user cost reduction over the period 2000-2007, and the second component simulates the projected evolution of R&D starting in 2008. In the first part, they find an elasticity of R&D with respect to its user cost around -0.4. The simulations indicate a large increase in R&D, but a slow adjustment to the new long run equilibrium. Harris et al. (2009) estimate the impact for Northern Ireland and find a long run user cost elasticity of -1.36.

Czarnitzki et al. (2011) use the nonparametric matching approach, exploring the effect of the Canadian Federal and Provincial R&D tax credits on a set of outcome variables, such as the share of innovative products in sales, 'new-to-the-world' innovations and some proxies for the impact of the innovation on the firm. They find significant positive effects of the tax credits on the number of new products and their sales, while they do not find any effect on the firm's profitability or market share. Corchuelo and Martinez-Ros (2009) evaluate the effects of the tax incentive scheme for R&D in Spain, also using a nonparametric matching estimator and propensity score matching, finding that the tax incentives have a positive and significant effect on R&D for large firms.

Our study focuses on the medium sized firms around the size threshold for eligibility to the SME scheme, and finds that the treated firms increased their R&D spending by about 18 percent in response to the policy intervention. After the introduction of the large company tax incentive scheme, the gap between treatment and control group R&D spending has widened (Figure 10). This is indicative of the tax incentive having helped to counter a decreasing trend in R&D investment by firms that remained above the size threshold for eligibility to the SME tax incentive scheme. For medium sized firms, the policy is found to have generated an additional £3.85 in R&D for every pound foregone in corporate tax revenues.

Where the data is available, measuring innovation outputs is beneficial to overcome concerns about relabeling and inflated salaries for scientists and researchers. Goolsbee (1998) and Rogers (2010) warn that with the introduction of tax incentives, the majority of increased R&D expenditures may go to higher salaries for scientists and engineers, rather than to a larger number of researchers. Goolsbee (1998) documents this finding by demonstrating that there is a relatively stable supply of scientists, with expenditure on pay rising significantly following increases in government subsidies to support R&D expenditure by firms. For subnational credits, another concern is the geographical shift of R&D activity away from high tax jurisdictions to those states with a more generous tax treatment of R&D (Wilson (2009)), essentially resulting in a zero sum game. Wilson finds a long run elasticity of R&D with respect to its user cost around -2.5, but this is offset by an out-of-state user cost elasticity of around +2.5.

Many studies underline the issue of relabeling ordinary expenses as R&D but the extent of the problem has rarely been quantified. Evidence on relabeling is provided in an early report by the US General Accounting Office (GAO (1989)). In their study based on the financial reports of 800 large US corporations, US GAO finds that around 20 percent of revenue agents are not convinced by the clarity of the definition of qualifying expenses. A more recent US GAO study dated November 2009 (GAO (2009)) lays out the main expenditure items which are more difficult to monitor for the tax authority. On the top of their list is the proportion of salaries paid to management level staff who supervise research activities. The report is based on interviews with the parties involved in the accounting of R&D for tax purposes, namely, officials from the Internal Revenue Service (IRS), taxpayers and tax consultants, and identifies large differences between the opinions of all involved parties regarding the identification of qualifying expenses. While relabeling is an important obstacle in identifying the true effect of R&D tax incentives, there are now high penalties for misreporting in the United States and other developed countries, and tax authorities have advanced their practice of monitoring eligible expenses over the years of implementation. In the 2009 GAO report, it is argued that IRS is very stringent in determining the share of qualifying research expenditure especially for the salaries of management level staff.

3 Data

3.1 Available data sources

In the UK, only a limited group of companies and the firms above a certain size threshold are required to disclose R&D expenditure in company accounts[11]. As a result, data on R&D expenditures by smaller enterprises is rather scarce. A list of data sources for UK R&D is presented in Table 1 below, which is reproduced from Office for National Statistics (ONS) Guidance Notes dated 13 November 2012 (Steer (2012)).

Table 1: Data sources for R&D in the UK

Dataset	Source	Definition of R&D
Business Enterprise R&D (BERD)	Survey	Frascati Manual
Gross Expenditure on R&D (GERD)	Survey	Frascati Manual
Northern Ireland GERD	Survey	Frascati Manual
Defence Statistics	Survey	Frascati Manual
R&D Tax Relief and Credit	Administrative	Other
R&D Scoreboard	Administrative	Other

Source: Office for National Statistics (Steer (2012)), own contribution

As can be seen in the table, there are only a handful of data sources on R&D available at the firm level. Out of these resources, only the R&D Scoreboard data published by the Department for Business, Innovation and Skills is in public domain, and this provides information only on the largest spenders on R&D[12]. To conduct an analysis of the firms around the size threshold of interest for us, the only data sets available are the BERD data by the ONS and the administrative data on R&D Tax Relief by the HMRC. Only the ONS data set goes back long enough in time for us to exploit the discontinuity in 2002 which is the introduction of the large company scheme[13].

[11]SSAP 13 provides guidance on the accounting rules for research and development. Paragraphs 19 and 20 of this document explain the rules for disclosure of R&D expenditure in the profit and loss accounts of the firm. Disclosure is limited to: "...public limited companies, or special category companies, or subsidiaries of such companies, or which exceed by a multiple of 10 the criteria for defining a medium sized company under the Companies Act 1985. (Statement of Standard Accounting Practice No.13, Revised January 1989)"

[12]Department for Business, Innovation and Skills announced in 2012 that the collection of R&D Scoreboard data was discontinued.

[13]In a separate project we examine results from a later reform using the administrative data and make comparisons, but this is not possible for the 2002 reform.

The Business Enterprise Research and Development (BERD) survey is conducted by the ONS, with the purpose of collecting the aggregate and sectoral UK BERD statistics. Recently, the micro level BERD data has been available under secure conditions for approved research projects.

ONS follows the Frascati Manual (OECD (2002)) methodology to collect the statistics on Business Enterprise Research and Development. The sampling frame for this data uses the Annual Business Survey (ABS) as its major source to identify R&D performing firms that employ more than 50 employees. Other main data sources include the UK Innovation Survey, new R&D sector firms from the Business Register, information from the Department for Business, Innovation and Skills (BIS), International Trade in Services R&D Exporters data and HMRC data on firms which claim R&D tax credits.

The micro level BERD data set can be merged with other ONS data sets such as the Annual Respondents' Database (ARD 1973-2009; previously, the Census of Production) and the Business Structure Database (BSD 1997-2011; snapshot of the Business Register) to obtain a match with the firm-level characteristics used as controls in this study. Because employment and turnover growth rate control variables are sourced by the Business Structure Database, the first year in the merged data set needed to be 1998. These data sets are available in different statistical units. BSD is provided at the 'enterprise level' which is the smallest autonomous unit in a firm with own decision-making capability. BERD and ARD data are collected at the 'reporting unit' level, which is where the postal address of the firm is registered. The reporting unit is smaller than an enterprise, but the majority of the enterprises are made up of only a single reporting unit. An enterprise group encompasses one or more enterprises, all legally connected to each other. The analyses in this paper are carried out at the enterprise level. These units are explained in more detail in Appendix A.1, which also explains the data cleaning procedures. The clean merged data set is available for the period 1998-2008[14].

ONS uses stratified sampling to select the enterprises which will receive a BERD questionnaire form each year. There are two types of BERD questionnaires, namely, the long form and the short form questionnaires. A long form questionnaire is sent each year to around 400 largest spenders in R&D, and this form asks for detailed information about the breakdown of the respondent's R&D spending into different categories. For the remaining reporting units, a stratified sampling procedure is used to select the ones that will receive a short questionnaire form, which includes a summary set of questions, such as total R&D spending (in-house and contract R&D) and R&D employment (See Appendix A.2 for further detail).

The micro BERD data set contains all the reporting unit-year observations that were identified by the ONS as performing R&D in a given year. The observations that are left outside of the stratified sampling have imputed values for the questions that are not answered, using the mean values of the

[14]The datasets used in this study were made available by the Office for National Statistics (ONS) and the Secure Data Service (SDS).

variable as a share of employment in the size band-sector cell. To avoid introducing measurement error, we refrain from using these imputed values. Details on the severity of the measurement error caused by the imputed values are presented in Appendix A.2. For enterprises with multiple reporting units, only those that have all associated reporting units with non-imputed values have been kept.

BSD contains the most complete information on employment, turnover, enterprise groups (ownership data), sector and other firm characteristics that are sourced by the Inter-Departmental Business Register (IDBR) and it is available at the enterprise level only. In the IDBR and hence the BSD, observations on enterprises are constructed using the data from HMRC on VAT traders and PAYE employers.

3.2 Selection of treatment and control groups

We selected treatment and control groups based on the threshold for eligibility to the SME Tax Relief. In the period of introduction of the large company scheme (2002), eligible SMEs which were already benefiting from the SME Tax Relief are assigned to the control group, which consists of enterprises just below the SME size threshold. This means enterprises that have between 100 and 249 employees, and are not owned by a group that has more than 249 employees or, when aggregated, the total number of employees in group member enterprises do not add up to more than 249. The treatment group is composed of enterprises just above the SME employment size threshold; with employment between 250 and 400, which may or may not be owned by a larger group. The interval of 100-400 employees is chosen specifically because it constitutes a size band used by ONS in their stratified sampling procedure, which determines the enterprises that will receive a questionnaire form in a given year (See Appendix A.2). In the 100-400 size band, enterprises are sampled at a ratio of 1:3, and this helps us in maintaining a roughly similar number of enterprises in each of the treatment and control groups.

For firms' eligibility to the SME tax credit, which places them to the control group, there are two more criteria that are not used here. If the firm has fewer than 250 employees (in aggregate), then it is subject to the asset/turnover test. According to the EC recommendation applicable to this incentive scheme, the size threshold to define an SME is for the enterprise to have fewer than 250 employees AND either less than 40 million Euros of turnover OR less than 27 million Euros of balance sheet size. The enterprise should also not be linked to a larger enterprise which does not possess these properties which define an SME. The reason for not undertaking the asset and turnover tests is because there is no data available on assets or group level turnover. Regarding the turnover criterion, simply summing the enterprise turnover values to obtain the enterprise group level turnover is not a valid method of calculating consolidated group level turnover. Nevertheless, the results are verified with a robustness check that defines the treatment group using both the employment and this approximation to the turnover criteria[15].

Defining the treatment group based solely on the employment measure only affects the composition of the control group, and allows all observations in the treatment group to be those classified as large enterprises by the EC recommendation. The control group however may contain some treated firms, since having a total of fewer than 250 employees does not guarantee SME status, if the enterprise fails both the asset and the turnover tests. This limitation does not jeopardize identification, but it reduces power while testing the null hypothesis of no effect of the tax incentive in the specifications presented later.

The reporting period for BERD is the calendar year. If the reporting unit does not have the record covering the calendar year, for instance year t, then the record for a business year that ends between April 6th of period t and April 5th of period $t+1$ is reported for the expenditure in year t. The Large Company Tax Relief was introduced in April 2002, which is three months into calendar year 2002 but earlier than 2003. If a firm's accounting year begins on any date later than the UK fiscal year, which runs between April 6, 2002 and April 5, 2003, then the R&D spending which is made in 2002 after the introduction of the R&D tax credit for large companies will be included in the company's BERD returns for 2003. For example, if Company A's accounting year runs between July 1, 2002-June 30, 2003, then all the R&D expenditure of Company A carried out between these dates would be recorded in the BERD returns for 2003. If, on the other hand, Company B's accounting year runs between April 1, 2002-March 31, 2003, then the R&D expenditure of Company B that was carried out between these dates would be recorded in the BERD returns for 2002.

In the corporation tax returns, all the qualifying R&D can be used to claim tax credits in the 2002-2003 fiscal year (depending on eligibility). If the firm's accounting year coincides with the calendar year, then the R&D reported for 2002 in BERD reflects exactly the expenditure incurred in 2002, and the company may claim tax credit on three quarters of the qualifying expenditure made in 2002, as the eligible expenditure will be apportioned for the period April 1, 2002-Dec 31, 2002.

Based on a number of company interviews and case studies, a qualitative HMRC review of the R&D tax credit states that the take up has been low in the beginning of the scheme due to lack of awareness by the firms (Michaelis et al. (2010)). Even for the companies that were aware of the tax credit, they may have been inclined to delay their undertaking of R&D to the following year given the apportionment of the tax credit in the first year of implementation, demonstrated in the example above. Based on these information, we selected calendar year 2003 as the first implementation period for analysis. It may be argued that the inclusion of R&D spending during 2002 as part of the pre-reform period is problematic because companies may be apportioning some of the R&D done in the 2002-2003 fiscal year to R&D recorded in calendar year 2002. We later show in Section 4.2 that the results are not sensitive to the removal of 2002 from the sample.

[15] The results from these regressions are not included in the paper.

While running the regressions, the sample is further limited to observations which are identified as 'active' in the BSD, in the manufacturing sector, with reported R&D expenditures above £10,000. For eligibility to any tax relief, companies needed to spend at least £10,000 until 2013. Table 2 presents the number of observations that remain in the sample after all filtering.

There are two sources of information on sectors in the BERD data set: (i) sector of R&D information returned only by long form respondents, and (ii) sector of activity sourced by the business register, which is available for both short and long form recipients. In the size band of interest for this study, that is the 100-400 employee size band, observations are mainly based on short form responses and therefore the sector of R&D information is not available. To maintain consistency across short form and long form recipients, the two digit sector of activity information in BERD is used instead of the two digit sector of R&D activity, which is only available for the long form recipients.

There is a small subset of long form recipients which fall in the size bands of interest for this study (fewer than 1000 enterprise-year observations) and comparisons between sector of activity and sector of R&D for this small group is informative for verifying the association between the two different sector variables. Regarding the broad split into manufacturing and services using the two digit sector of activity in comparison to using the two digit sector of R&D, for more than 65 percent of the observations, the two variables are in agreement. For the remaining observations, it is most common to observe a services sector flag according to the sector of activity matched with a flag for manufacturing by the sector of R&D. These firms are usually R&D labs which operate in the SIC sectors 'scientific research and development' and 'computer programming, consultancy and related activities'. Robustness checks which include additional observations on these firms confirmed the main results, which used only firms classified as manufacturing by their sectors of activity and hence excluded these service sector firms.

Table 2: Number of observations, treatment and control groups across years

period	1998	1999	2000	2001	2002	2003	2004	2005	2006
control	111	180	178	162	125	160	277	148	152
treatment	154	274	218	214	161	164	274	145	121

A key aspect is that, due to the stratified sampling procedure, the micro BERD data covers different enterprises in the treatment and control categories in each of these years. It is not necessarily the case that the same enterprise is observed both before and after the reform, as a genuine panel cannot be constructed in this stratum. Most of the observations are only observed in either the pre-treatment or the post-treatment periods.

3.3 Variables and deflators

The main regressions reported in Tables 4 and 5 in the Results Section use real expenditures on R&D which is obtained by deflating the nominal intramural R&D expenditure from the BERD data set using a weighted deflator with 50 percent weight on researcher salaries and 50 percent weight on the GDP deflator. Intramural R&D here means the in-house R&D carried out by the company by its own employees. The researcher salaries component of the weighted deflator is taken from the Annual Survey of Hours and Earnings (ASHE) tables on gross annual pay for science and technology professionals (Table code 2.7a, job code 21). The GDP deflator is obtained from the OECD Economic Outlook 'pgdp' series (base year 2008). In the R&D literature, this kind of weighted deflator is commonly used to reflect the fact that around 50 percent of R&D investment goes to the salaries and wages of research staff (See, for instance, Bloom et al. (2002)). Data on turnover and employment is obtained from the BSD. Turnover controls (both levels and growth rates) are deflated using the manufacturing output component of the UK producer price index series (JVZ7).

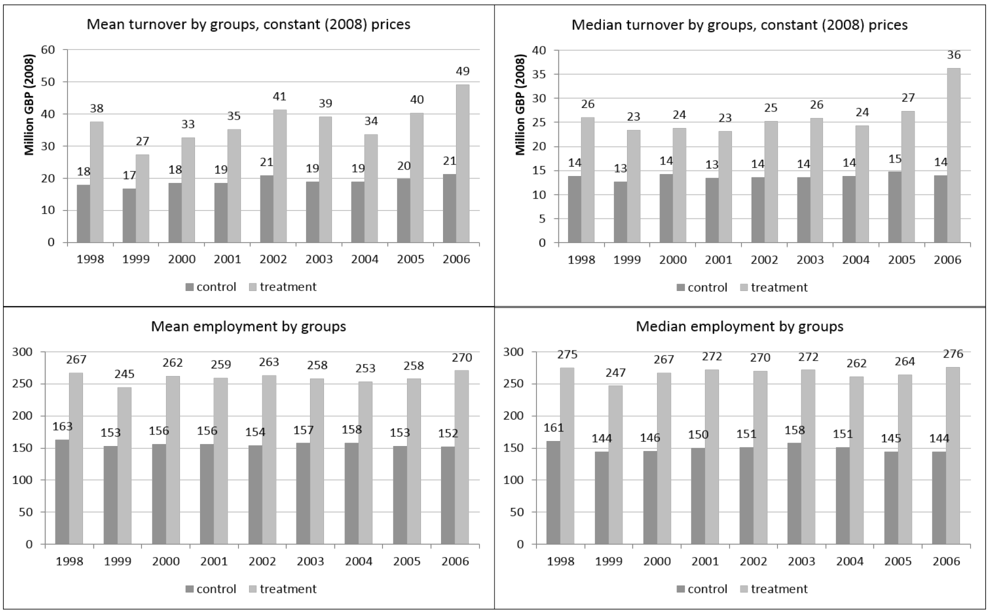
3.4 Descriptive statistics

Identification with the difference-in-differences estimator requires that in the absence of treatment, we should expect the change in the outcome variable between pre- and post-intervention periods for the control group to be equal to the change in the outcome variable for the treatment group. The counterfactual for the treatment group is not observed, but the trends in other variables may indicate if there is a large differential change between pre- and post-intervention periods for the treatment and control groups. Reliable information on employment, turnover and sector is available thanks to the BSD. Trends in turnover and employment can be observed in Figure 7[16]. The levels of enterprise employment and turnover are naturally very different for the treatment and control groups, but here the point is to see whether there is a large differential change or not, which does not seem to be the case around the periods 2002 and 2003.

The sectoral compositions across treatment and control groups are presented in Table 3. For our purposes, it is important to have a similar distribution of high tech, medium tech and low tech firms in the pre- and post-intervention periods across treatment and control groups. One way of identifying this is to use the OECD technology classifications that are laid out in OECD (2003) based on the average R&D intensity of relevant two, three or four digit sub-sectors of activity in manufacturing. In order to establish a classification of this kind for our sample, we use the R&D intensities of the two digit sectors available in our own data. The correspondence between the OECD high, medium

[16] The bottom graphs in the figure show mean and median employment for treatment and control groups at the enterprise level; therefore, the values may remain below the threshold level of 250 even for the treatment group, as the determining criteria for eligibility to the SME credit considers enterprise group employment.

Figure 7: Comparison of treatment and control groups



high, medium low and low technology sectors with our classification can be observed in Table 9 in Appendix A.2. There are no large discrepancies between the two classifications.

First, we identify each observation in the sample as 'above' or 'below' the overall median R&D intensity. We then categorize each two-digit sector as 'high', 'medium' or 'low' R&D intensity, where the 'high R&D intensity' group has more than 65 percent of observations above the median, 'medium R&D intensity' group has between 40 to 65 percent of observations above the median and 'low R&D intenstiy' group has fewer than 40 percent of observations above the median. Table 3 demonstrates that there is some significant change in sectoral compositions between pre- and post-treatment periods. In Table 3, the percentages represent the share of observations in a given cell in high, medium and low technology sectors, where a cell can be one of the following: (i) control group pre-treatment, (ii) control group post-treatment, (iii) treatment group pre-treatment, and (iv) treatment group post-treatment. It can be observed in the table that the share of observations belonging to high technology sectors has increased in the control group over time from 24 to 31 percent, whereas in the treatment group, there is no such increase, and conversely the share of medium technology sectors decreased in the control group from 44 to 36 percent. These compositional changes relate to the fact that the samples of treatment and control group enterprises available are not genuine panels. This demonstrates the potential importance of controlling for sectors in the estimation stage. Table 9 in Appendix A.3 provides further evidence for such changes over time at the more detailed two-digit sector level.

There may be several reasons underlying the increase in the share of high technology firms in the control group. First of all, this may be a reflection of a compositional shift in the whole economy, outlined in Section 2.1. The reallocation towards higher technology sectors of manufacturing may

Table 3: Share of observations in high, medium and low intensity of R&D sectors

R&D intensity:	high		medium		low	
	control	treat.	control	treat.	control	treat.
1998-2002	24%	24%	44%	42%	32%	34%
2003-2006	31%	24%	36%	39%	33%	37%

Figure 8: Share of UK enterprises in high, medium and low technology sectors for medium size bands

be taking place more intensively at the lower end of the firm size distribution, with the smaller low productivity firms dropping out faster than the larger ones. Alternatively, the observed sectoral shift in the control group may merely be an artifact of the sampling procedure for the BERD data set.

The Business Structure Database (BSD) allows for a further investigation of the shift in the sectoral composition of the UK manufacturing sector by size bands. Comparing the distribution of enterprises across high, medium and low technology sectors for the 100-249 employee size band with that for the 250-399 employee size band is informative in finding out whether the patterns observed in the BERD sample are a reflection of broader trends in the economy. Figure 8 demonstrates that such reallocation effects across our size bands of interest are not very pronounced, at least for the period that can be studied using the BSD data available.

The difference-in-differences estimator aims to capture the average or expected impact of the intervention on the treatment group, that is, it aims to estimate:

$$\{E[Y|t > 2002, D = 1] - E[Y|t \leq 2002, D = 1]\} - \{E[Y|t > 2002, D = 0] - E[Y|t \leq 2002, D = 0]\} \quad (4)$$

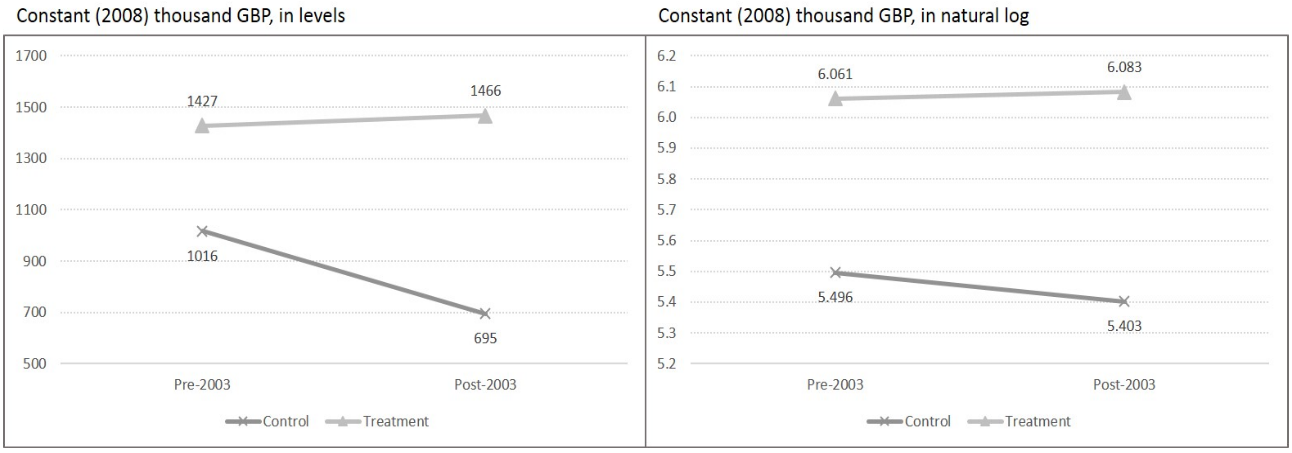
where

$$D = \begin{cases} 1, & \text{if treated} \\ 0, & \text{if control} \end{cases} \quad (5)$$

t represents the year and Y stands for the outcome of interest, in our case, it is the R&D investments made by the sample enterprises.

The sample analogue of the expression in Equation 4 compares differences in means between pre- and post-intervention periods across treatment and control group observations. Figure 9 presents the mean R&D spending in each of these cells. In the subsequent analysis, we use the natural logarithm to have a percentage change interpretation, and the shape of the graphs look similar if we use the natural logarithm of R&D spending instead of the levels. These cell means simply correspond to the coefficients in a diff-in-diff regression without any controls. In a regression sense, the diff-in-diff coefficient captures the additional R&D generated thanks to the policy intervention, after having accounted for any treatment-specific or control-specific effects as well as common trends. In the figure, it can be observed that there is a differential change between the two groups, mainly owing to a fall in the control group R&D between the two periods, rather than a rise in the treatment group R&D. If the specification with no controls were correct, then it suggests that the policy intervention may have prevented a greater decline in R&D around the size threshold of interest for this study. The trend in the average R&D spending by control and treatment firms are presented in Figure 10, showing the widening gap between treatment and control group firms after the introduction of the R&D tax credit.

Figure 9: R&D spending across treatment and control groups, pre- and post-2003



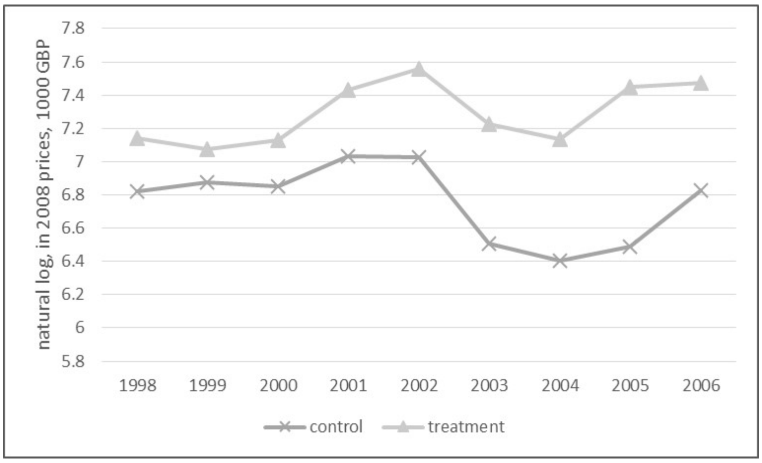
4 Results

4.1 Model

We estimate the following base model:

$$r_{it} = \gamma + \delta_D D_i + \delta_T T_t + \delta_I D_i T_t + x'_{it}\beta_x + \nu_{it} \tag{6}$$

Figure 10: Comparison of treatment and control groups, mean R&D



where r_{it} is the natural logarithm of R&D spending of enterprise i in year t in 2008 prices, D_i is a dummy that takes on a value of 1 for treated observations, 0 for the control group, T_t is a dummy that takes on a value of 1 for years 2003 onwards and 0 otherwise. The coefficient δ_I on the interaction term D_iT_t thus captures any differential change in r_{it} between these two periods for the treatment group compared to the control group, and the null hypothesis of no impact of the introduction of the tax credit for larger firms corresponds to $\delta_I = 0$. We later drop T_t and include a full set of year dummies. x_{it} is a $K \times 1$ vector of controls, including sector dummies, sector-year interaction terms, employment, real turnover and their growth rates.

Table 4 presents the results from using this specification with different choices of controls. Column 1 presents the most simple specification with no controls, which replicates (in a regression sense) the right hand side picture in Figure 9. After the addition of each control variable, the sample size changes as some of these variables are only available for a more limited sample. In order to trace if the results change due to the reduced sample size or the addition of the control variable, regressions are run on the same sample with and without the controls and the results are presented in the column beside the one with the particular control variable(s).

The most important set of controls turns out to be the sector dummy variables. In Columns (1) and (3), the diff-in-diff coefficient is not significantly difference from zero, but in all regressions with sector controls, this coefficient is close to 0.2 and at least borderline significant at the 10 percent level. We saw in Table 3 above that the composition of the control group shifts towards more high tech sectors in the later period, and this illustrates the importance of controlling for this change.

The addition of turnover and employment variables at the same time, is our best proxy for controlling for productivity given the available data. In Column (6) of Table 4, the addition of the turnover and employment controls in levels induces a slight drop of the diff-in-diff coefficient from 0.23 (Column (7)) to 0.18 (Column (6)) and the t-statistic goes down from 2.0 to 1.7 as the estimate becomes more imprecise. In Columns (8) and (9), we control for turnover and employment growth rates. Column (9) results include both the levels and the growth rates of (the natural logarithm of) turnover and employment. The results in Columns (8), (9) and (10) require the availability of turnover and employment information from two periods back, and the effect of having a smaller sample size is reflected in the results in Column (10). Without introducing any employment and turnover controls, the reduction in sample size because of the increased data requirement in Column (10) reduces the t-statistic of the diff-in-diff coefficient to 1.85. The magnitude of the coefficient remains at 0.21. The addition of turnover and employment growth rate controls then induces a drop in the magnitude of the coefficient from 0.21 (Column (10)) to 0.18 (Column (9)), and the t-statistic drops to 1.6 as the estimate becomes more imprecise. The turnover variable is very jumpy and contains outliers, which were not removed from the sample to retain comparability across the results, but the addition of this variable increases the variance of estimated coefficients. The 95 percent confidence intervals for the estimates in Columns (8), (9) and (10) largely overlap.

In Table 5, this base model is then complemented by a specification which has R&D scaled by firm employment as the outcome of interest, with $r_{it} - l_{it}$ as the dependent variable (l_{it} denotes the natural logarithm of employment). This specification is more in line with the theoretical background, which is explained in Section 2.3 where it has been shown that:

$$lnR - lnQ = constant - lnU \tag{7}$$

Since we do not have information on Q, which is the firm's output, we can use the next best available firm size measure, that is the total employment of the firm. Turnover is also an alternative here, but as mentioned earlier, the turnover values exhibit high variation and do not seem to be a very reliable benchmark. Regression results with the turnover variable as an additional control have been included in Tables 4 and 5[17]. The results presented in Table 5 from estimating the model with R&D scaled by the firm size as the dependent variable are very similar to those in Table 4 in terms of both the magnitude and the significance of the diff-in-diff coefficients.

Having established that the sector level controls are important in the results, several variations of the model allowing for sector-specific difference-in-differences coefficients have been run. These specifications were of interest for comparing the micro level findings for the size band studied here with the aggregate trends discussed in Section 2.1. The null hypothesis of equal diff-in-diff coefficients for high, medium high, medium low and low technology sectors cannot be rejected. In aggregate data, on the other hand, the increase in R&D intensity appears to be driven by the high technology manufacturing

[17]In other specifications, the coefficient on the log of employment is allowed to differ from unity. In all cases where sector dummies are included, a significant differential effect of the tax incentive of around 17-23 percent is found in comparison to the counterfactual scenario. Since these results do not provide new insights, the tables have not been included in the paper.

sectors. In line with the basic neoclassical theory of R&D investment, our results suggest that the impact of the R&D tax credit was similar between high technology and lower technology sectors. If this is correct, it follows that other factors caused the composition of UK BERD to shift towards high technology sectors over this period. One explanation may be the increased competition from BRIC countries in lower technology sub-sectors of manufacturing, as discussed in Bloom et al. (2011), which induced a rise in the intensity of innovation in more high technology sectors in the UK. Such trends would be captured by the interactions between year and sector dummy variables in the micro analysis. Another explanation may be that the size band of interest for the purposes of this study (100-400 employees) is smaller than that where the bulk of R&D is performed (larger companies) and the trends may be different than at the upper end of the size threshold. Given that the share of UK manufacturing BERD which is conducted by the firms in the 100-400 employee size band is about 14 percent around the time period studied, this possibility cannot be ruled out.

Table 4: Results (I)

Dep.var: ln(R&D spending)	1	2	3	4	5	6	7	8	9	10
control, pre	5.496	4.998	5.399	4.972	6.234	-2.967	2.741	7.657	0.834	7.862
	(70.73)	(20.62)	(49.65)	(19.80)	(6.65)	(-3.36)	(3.61)	(3.77)	(0.37)	(3.82)
treated group	0.565	0.548	0.566	0.552	0.557	0.194	0.543	0.560	0.190	0.556
	(5.86)	(6.38)	(5.85)	(6.39)	(6.30)	(2.06)	(6.10)	(5.93)	(1.88)	(5.87)
post-reform period	-0.093	-0.164								
	(-1.10)	(-2.05)								
diff-in-diff	**0.115**	**0.224****	**0.123**	**0.227****	**0.212***	**0.184***	**0.228****	**0.214***	**0.179**	**0.213***
	(0.94)	**(2.05)**	**(1.01)**	**(2.06)**	**(1.89)**	**(1.70)**	**(2.03)**	**(1.86)**	**(1.61)**	**(1.85)**
ln(employment lag)						0.143			0.0585	
						(1.37)			(0.52)	
ln(real turnover lag)						0.506			0.594	
						(6.46)			(7.77)	
empl. growth (lag)								0.212	0.396	
								(1.97)	(3.33)	
turn. growth (lag)								-0.028	-0.204	
								(-0.52)	(-3.03)	
sector dummies	No	Yes	No	Yes	Yes	Yes	Yes	Yes	Yes	Yes
year dummies	No	No	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
sector*year	No	No	No	No	Yes	Yes	Yes	Yes	Yes	Yes
No of obs	3218	3218	3218	3218	3218	3199	3199	2902	2902	2902

t-values in brackets below the coefficient
standard errors clustered at the enterprise level

Table 5: Results (II)

Dep.var: ln(R&D per worker)	1	2	3	4	5	6	7	8	9	10
control, pre	0.479	-0.031	0.337	-0.0985	1.738	-4.672	-2.124	1.884	-0.928	2.082
	(6.34)	(-0.15)	(3.23)	(-0.45)	(1.83)	(-5.78)	(-3.01)	(0.92)	(-0.42)	(1.01)
treated group	0.097	0.086	0.097	0.088	0.094	0.007	0.078	0.095	0.025	0.091
	(1.05)	(1.04)	(1.04)	(1.06)	(1.11)	(0.08)	(0.91)	(1.04)	(0.26)	(0.99)
post-reform period	-0.091	-0.156								
	(-1.08)	(-1.99)								
diff-in-diff	**0.107**	**0.216****	**0.117**	**0.219****	**0.210***	**0.187***	**0.228****	**0.214***	**0.170**	**0.213***
	(0.90)	**(2.05)**	**(0.98)**	**(2.07)**	**(1.95)**	**(1.76)**	**(2.11)**	**(1.92)**	**(1.56)**	**(1.91)**
ln(employment lag)						-0.402			-0.515	
						(-4.31)			(-5.37)	
ln(real turnover lag)						0.470			0.561	
						(6.30)			(7.62)	
empl. growth (lag)								0.206	0.383	
								(2.07)	(3.56)	
turn. growth (lag)								-0.032	-0.205	
								(-0.66)	(-3.13)	
sector dummies	No	Yes	No	Yes	Yes	Yes	Yes	Yes	Yes	Yes
year dummies	No	No	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
sector*year	No	No	No	No	Yes	Yes	Yes	Yes	Yes	Yes
No of obs	3218	3218	3218	3218	3218	3199	3199	2902	2902	2902

t-values in brackets below the coefficient
standard errors clustered at the enterprise level

4.2 Robustness checks

The results presented in the preceding section are robust to estimating the model at the reporting unit level, using sectors of R&D rather than sectors of activity to define the manufacturing subsample and the sector dummy variables, and using the turnover criterion in addition to employment to define the treatment group.

Placebo tests have been run with a difference-in-differences variable for all other years available in the data, and no effect has been found in any other year than 2003. Had the effect been driven by the more productive firms that may be surviving in the treatment group differentially more than the control group, we would have observed a significant difference-in-difference in other years of the analysis as well.

The main concern in a policy setting where the announcement of the policy predates implementation is that beneficiaries may adjust their investment behavior after the announcement but prior to implementation to obtain the maximum gain from it. In the case of the R&D Tax Relief schemes in the UK, neither the SME nor the large company scheme came as a surprise for the firms that were going to benefit.

The expected behavior of a forward-looking profit maximizing firm would be to delay some R&D investment spending after the announcement until after the implementation of the policy, or maybe even until the firm's first complete tax year after the introduction of the tax credit, to avoid the apportionment of the benefit. For example, any R&D undertaken in the period January-December 2002 would attract only 75 percent of the credit, while R&D undertaken in January-December 2003 would attract 100 percent of the credit. Consultations for the large company scheme were launched with the 2001 Budget, a year prior to implementation (Figure 6). In this case one may observe a drop after the announcement but before the introduction of the policy, and then an overshoot of R&D investment shortly after the policy has been introduced as all the postponed investment would tend to be made in these early periods. If this were the case, then what we observe as the difference-in-difference effect could solely have been the reflection of postponement of R&D spending to a later date, rather than a genuine increase in R&D spending as a result of the policy.

The simplest way of assessing whether there has been any strategic delaying is to omit all the periods between announcement and the first period of implementation. In the context of the large company scheme, omission of the years 2002 and 2003 achieves this objective. Table 6 reports results for the same specifications presented in Table 4, but with observations for these two years excluded from the sample. The estimated impact of the introduction of the tax credit for larger firms remains very similar to that obtained using the full sample, suggesting an increase in R&D by approximately 19-22 percent. The smaller sample size results in a marginal reduction in the statistical significance of the estimated coefficient on the diff-in-diff interaction term, but there is no indication that our full sample results are seriously biased by firms postponing R&D expenditure until after the introduction of the tax credit in April 2002. Results with R&D per worker as the dependent variable reported in Table 7 are very similar to the finding in Table 6.

4.3 Discussion

The UK R&D tax incentive scheme has gradually become more generous, now with more than £1 billion cost to the Exchequer in foregone corporation tax revenue annually. The findings of this paper suggest a robust 18-23 percent increase in R&D spending after the enterprises in the treatment group became eligible for this tax incentive.

The ONS data allows us to estimate that the total R&D spending in the size band of interest for this study (100-399 employees) in 2003 by the manufacturing sector was about £747 million. Using micro level data on BERD, we can estimate that 68 percent of this, or £506 million, was done by the enterprises in the treatment group (250-399 employees). If our most modest estimate of an 18 percent increase applied to all R&D undertaken by manufacturing firms with 250-399 employees, then the additional R&D generated for this size group would have been about £77 million in 2003 prices.

From the estimate of 18-23 percent, one can back out the elasticity of R&D with respect to its user cost, utilizing the finding that the introduction of the large company scheme resulted in a reduction in the user cost of R&D by about 13 percent in the UK (Bond and Guceri (2012)). The lower bound of 18 percent increase in spending therefore corresponds to a user cost elasticity estimate of about -1.35.

Table 6: Robustness Checks (I) - 2002-2003 omitted, dep. var. real R&D (natural log)

	1	2	3	4	5	6	7	8	9	10
control, pre	5.484	2.236	5.596	4.86	6.234	-3.142	2.575	-0.428	-7.524	-0.542
	(66.76)	(9.10)	(55.24)	(15.61)	(4.79)	(-4.23)	.	(-0.36)	(-4.46)	(-0.44)
treated group	0.552	0.555	0.552	0.557	0.564	0.203	0.549	0.563	0.199	0.562
	(5.40)	(6.05)	(5.39)	(6.05)	(5.95)	(1.99)	(5.76)	(5.52)	(1.85)	(5.49)
post-reform period	-0.0847	-0.13								
	(-0.88)	(-1.44)								
diff-in-diff	0.16	0.221	0.171	0.225	0.211	0.191	0.226	0.221	0.19	0.217
	(1.17)	(1.81)	(1.25)	(1.84)	(1.69)	(1.58)	(1.80)	(1.71)	(1.53)	(1.67)
ln(employment lag)						0.128			0.0196	
						(1.09)			(0.15)	
ln(real turnover lag)						0.511			0.618	
						(5.86)			(7.50)	
empl. growth (lag)								0.254	0.463	
								(2.05)	(3.28)	
turn. growth (lag)								-0.0463	-0.231	
								(-0.74)	(-3.21)	
sector dummies	No	Yes	No	Yes	Yes	Yes	Yes	Yes	Yes	Yes
year dummies	No	No	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
sector dummies*year	No	No	No	No	Yes	Yes	Yes	Yes	Yes	Yes
No of obs	2608	2608	2608	2608	2608	2594	2594	2311	2311	2311

t-values in brackets below the coefficient
standard errors clustered at the enterprise level

Table 7: Robustness Checks (II) - 2002-2003 omitted, dep. var. real R&D per worker (natural log)

	1	2	3	4	5	6	7	8	9	10
control, pre	0.465	-2.576	0.576	-0.207	1.857	-4.865	-2.04	-5.584	-9.486	-5.701
	(5.82)	(-6.72)	(5.72)	(-0.79)	(1.41)	(-7.93)	.	(-4.74)	(-6.08)	(-4.75)
treated group	0.090	0.099	0.089	0.100	0.106	0.024	0.088	0.102	0.033	0.101
	(0.92)	(1.12)	(0.90)	(1.12)	(1.16)	(0.25)	(0.97)	(1.04)	(0.33)	(1.03)
post-treatment period	-0.0763	-0.115								
	(-0.81)	(-1.29)								
diff-in-diff	0.142	0.202	0.154	0.206	0.197	0.179	0.214	0.208	0.169	0.204
	(1.06)	(1.71)	(1.16)	(1.75)	(1.64)	(1.52)	(1.78)	(1.68)	(1.39)	(1.63)
ln(employment lag)						-0.422			-0.553	
						(-4.08)			(-5.27)	
ln(real turnover lag)						0.475			0.591	
						(5.82)			(7.61)	
empl. growth (lag)								0.264	0.457	
								(2.29)	(3.58)	
turn. growth (lag)								-0.057	-0.234	
								(-1.02)	(-3.36)	
sector dummies	No	Yes	No	Yes	Yes	Yes	Yes	Yes	Yes	Yes
year dummies	No	No	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
sector dummies*year	No	No	No	No	Yes	Yes	Yes	Yes	Yes	Yes
No of obs	2608	2608	2608	2608	2608	2594	2594	2311	2311	2311

t-values in brackets below the coefficient
standard errors clustered at the enterprise level

5 Conclusion

The number of countries which offer R&D tax incentives to stimulate business R&D spending has been increasing rapidly in the past few decades. After a long period of relative decline in aggregate R&D intensity, the UK joined the group of countries which offer generous fiscal incentives for R&D in 2000 with the introduction of the SME Tax Relief Scheme, followed by the large company scheme in 2002. In this study, the gap in the timings of these two policies was utilized to obtain difference-in-difference estimates of the impact of the large firm tax credit on those large firms that are closest in size to the largest SMEs, which were already benefiting from the SME scheme when the large company scheme was introduced.

Tax credits have a direct effect on the user cost of R&D capital, or the required rate of return from the marginal R&D project which is just sufficient for the project to be commercially viable. Based on the neoclassical optimal capital accumulation framework, an inverse relationship between the user cost of R&D and the firm's investment in R&D can be expected. Motivated by this theoretical background, the empirical specifications in this paper examined the effects of the introduction of the large company tax credit scheme on R&D spending and on R&D per worker at the enterprise level.

Controlling for firm size and growth using employment and turnover, more importantly, for changes in the sectoral composition of our samples using dummy variables for two digit sectors of activity (and their interactions with time), we found that treatment group companies which started to benefit from the large company scheme in the 2002-03 fiscal year increased their R&D spending by around 18 percent in comparison to the control group after the introduction of the policy. The announcement of the scheme pre-dated implementation by about a year; therefore, we conducted robustness checks to verify that the effect found in this study was not simply a result of the postponement of R&D spending to the period after the introduction of the scheme.

The robust 18 percent increase over the counterfactual scenario of no tax credits for large firms corresponds to an elasticity of R&D with respect to its user cost of around -1.35. If we assume that the estimate of an 18 percent increase applies to all R&D undertaken by manufacturing firms with 250-399 employees, then the additional R&D generated for this size group would have been about £77 million in 2003 prices. Given that the total cost of the large company scheme to the Exchequer was £340million, and assuming that the treated firms in our sample would be responsible for the same share of the cost as their share in total R&D, we may argue that the firms in our treatment group was responsible for a cost of about £20 million in foregone taxes. This then translates to the generation of an additional £3.85 in R&D per pound foregone in taxes.

According to our findings, the UK R&D tax incentive scheme has been successful in generating a considerable amount of additional R&D spending by the business sector. Further research may seek to shed light on the decomposition of this improved performance into different expenditure items such as researcher salaries and newly hired researchers, using more detailed data.

A Data appendix

A.1 Data cleaning

BERD data is available at the 'reporting unit' level, which corresponds to the geographical unit that has the postal address of the firm. The reporting unit may or may not be larger than a 'local unit', therefore it may be larger than a single plant or a single R&D lab. It may be attached to the headquarters or can be a separate unit. A slightly larger statistical unit than the reporting unit is the 'enterprise', which is defined in the EU Regulation on Statistical Units (EEC 696/93) as "...an organizational unit producing goods or services, which benefits from a certain degree of autonomy in decision-making, especially for the allocation of its current resources...". BERD observations have the reporting unit as their identifier and most of them also contain the enterprise reference number. Missing values for the enterprise references in BERD have been filled using the ARD, which contains both the reporting unit and enterprise reference numbers. Other information in ARD has not been used due to the low overlap between the BERD and ARD stratified sample for firms in the size range which is the main focus of this study.

An 'enterprise group' is defined as "an association of enterprises bound together by legal and/or financial links. A group of enterprises can have more than one decision-making centre [...]. It constitutes an economic entity which is empowered to make choices, particularly concerning the units which it comprises (EEC 696/93)". The definition of an enterprise group is important for our purposes, as assignment to the control group depends on whether the group as a whole satisfies the criteria for eligibility to the SME scheme.

Reporting unit level R&D data in BERD is aggregated to the enterprise level to match with BSD. For enterprises with multiple reporting units, only those that have all associated reporting units with non-imputed values have been kept. The procedure of removing reporting units with imputed values reduced the sample size substantially, while the fact that all reporting units needed to be aggregated to the enterprise level did not seriously worsen the reduction in sample size.

Similar to ARD, BERD provides information on both the reporting unit and enterprise references for each observation, but around a total of 40,000 observations appear to be missing the enterprise reference numbers in BERD for the years included in this study[18]. To remedy this problem, the ARD dataset was used, completing a significant portion of the missing enterprise references in BERD. This was possible, because the micro level ARD dataset with some basic information is available for all observations, even if they are not selected for sampling in a given year. Other information in ARD than the reporting unit-enterprise reference mapping was not used, as the sampling ratios in ARD are different from those in BERD for the size range of interest in this study and we did not observe

[18]By an observation, here we mean a unique reporting unit-year combination.

sufficient overlap between sampled observations in BERD and ARD in the relevant size range[19].

In order to match the data with the business register, it was necessary to sum reporting unit values to the enterprise level as BSD is provided at the enterprise level, which is also a more meaningful economic unit in comparison to the reporting unit to run the analyses. Nevertheless, we later ran robustness checks at the reporting unit level and observed that the results were not highly affected by the change in units. Table 8 presents the number of observations left in various data cleaning steps. The number of non-imputed observations are also presented in this Table, where it can be seen that sampled enterprises constitute a small fraction of total enterprises which were identified as conducting R&D. Appendix A.2 provides further information about the imputed values in the BERD data set. In the Table, the number of enterprises which only have one reporting unit, and the number of enterprise groups that only have one enterprise are provided to give an idea about the group structures, and also the large overlap between the reporting unit and the enterprise.

Table 8: Number of reporting units and enterprise references across years

Year	1998	1999	2000	2001	2002	2003	2004	2005	2006
All BERD, total rows	14,906	14,226	16,272	15,666	19,407	17,141	19,384	20,364	24,251
All BERD, total real responses	2,037	3,168	3,051	3,103	3,132	3,017	3,166	3,036	2,769
Unique rep unit year obs in BERD	9,197	8,544	9,515	9,506	11,896	10,334	12,783	13,874	18,018
Unique rep unit year real responses in BERD	1,369	2,384	2,344	2,472	2,483	2,519	2,641	2,529	2,252
Rep units singly attached to an enterprise	8,552	7,920	8,645	8,850	10,945	10,064	12,361	13,186	17,552
Total BERD represented by the rep units singly attached to an enterprise	76%	80%	81%	77%	85%	80%	69%	69%	74%
Unique entref year obs in collapsed BERD	8,622	7,987	8,729	8,937	11,055	10,167	12,529	13,301	17,672
Number of entref year observations with all non-imputed rep unit observations	1,296	2,303	2,248	2,383	2,342	2,406	2,492	2,389	2,094
Number of entref year observations with all imputed rep unit observations	7,292	5,654	6,437	6,509	8,646	7,702	9,978	10,853	15,516
Number of entref year observations with some imputed rep unit observations therefore needed to be dropped	34	30	44	45	67	59	59	59	62
Number of entref year observations with all non-imputed rep unit observations-all unmatched entrefs to BSD	1,232	2,239	2,186	2,300	2,268	2,317	2,440	2,279	2,060
Unmatched to BSD	64	64	62	83	74	89	52	110	34
Number of enterprise groups in the resulting data set	1,059	1,949	1,975	2,127	2,114	2,178	2,244	2,164	1,944
Enterprises singly attached to an enterprise group	972	1,797	1,846	2,014	2,008	2,080	2,118	2,089	1,861
Number of groups with more than a single enterprise	87	152	129	113	106	98	126	75	83
Total BERD represented by enterprises singly attached to an enterprise group (within this 'non-imputed, BSD-matched' data set	59%	44%	54%	69%	67%	74%	80%	86%	77%
Filter further to, real R&D> £10K and non-missing; number of enterprises	1,188	2,095	2,041	2,152	2,163	2,192	2,316	2,162	1,965
Filter further to real R&D> £10K and non-missing, active, employment size band 100-400; number of enterprises	347	598	523	517	442	472	730	485	448
Filter further to real R&D> £10K and non-missing, active, employment size band 100-400 and manufacturing; number of enterprises	265	454	396	376	286	324	551	293	273

A.2 Imputed values in BERD

For the analyses in this paper, the BERD data set has some drawbacks, which arise from its sampling procedures. There are two types of questionnaire forms sent out to firms: a long form and a short form. About 400 largest spenders (those who spent more than £3 million in the given year) on

[19]ARD contains important information such as gross value added and other variables from the Annual Business Inquiry.

R&D receive a long form questionnaire, and the rest receive a short form questionnaire. This latter form contains a small set of questions tracing basic information such as the unit's: (i) in-house R&D expenditure, (ii) extramural R&D expenditure, (iii) full time equivalent number of R&D personnel, and (iv) total headcount on R&D. In the micro level data set, unfortunately there is no short-form based information on the number of R&D personnel or total headcount on R&D. The long form collects a much wider set of variables, including a breakdown of R&D expenditure to product groups; capital and current expenditure, broken down into salaries and other current expenditure; sources of funding for R&D; a breakdown of the skills set for R&D employment; and a breakdown of R&D expenditure into geographic locations (UK postcodes). As smaller firms tend to spend less on R&D than larger firms, the information available on SMEs is mostly limited to the questions asked in the short form.

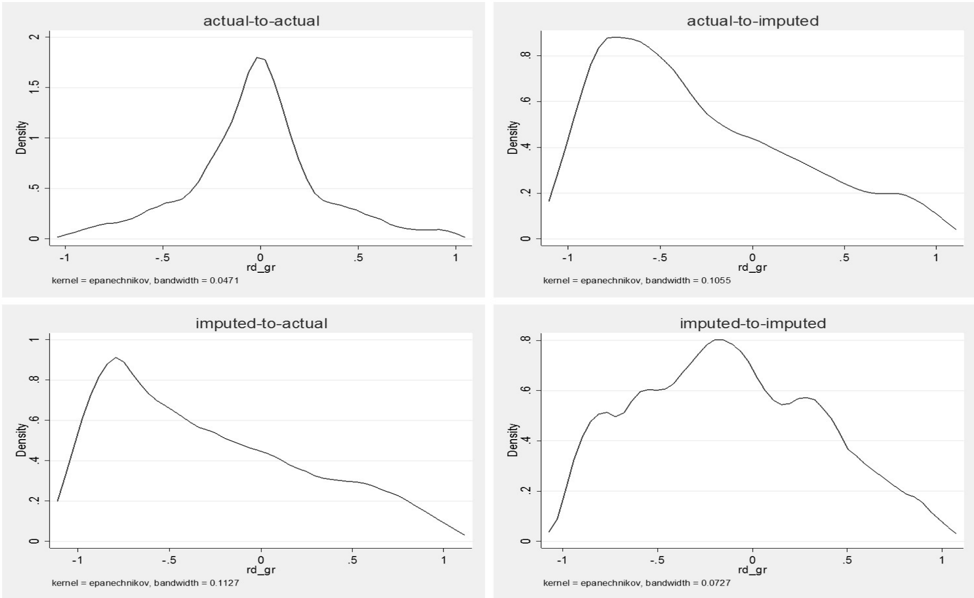
The group of smaller firms (as they are less likely to be among the top 400 spenders) are subject to sampling at different sampling fractions depending on their size measured by employment. Since the stratified sampling procedure is repeated every year, this causes many gaps in the time series data, making it difficult to obtain a clean panel structure with the same firm being followed across time. Based on the publicly available BERD First Release data[20], the breakdown of participants to BERD Inquiry into long and short form recipients is around 4000 sampled firms, out of which around 400 are sent a long form and the rest are sent a short form. Out of the firms which receive short forms, all those with more than 400 employees are sampled. In our size band of interest, which has firms with 100-400 employees, the sampling ratio is 1:3. The smallest firms, that is, those with less than 100 employees are sampled with a 1:4 ratio.

When aggregating the data for the BERD publication, the ONS imputes the values for the unsampled firms based on their employment number and product group. In each of the 99 product group-size band 'cells' available (33 product groups over 3 size bands), the values for the unsampled observations are imputed using the average R&D per worker value of those observations which are not imputed, with employment as the scaling variable. For instance, if an unsampled firm in sector H (Pharmaceuticals) and size band 2 (100-400 employees) has "x" employees (this information is available through the IDBR for all firms), their unknown in-house R&D spending is imputed as the mean R&D per worker in that cell multiplied by the employment number "x" of the observation. This imputation procedure introduces a high level of variation across years for a given reporting unit when the micro panel version of the data set is used. The variance of the growth rate in R&D spending from one year to the next increases significantly between two years of data when these are imputed, and also when one of the two values is imputed. Figure 11 demonstrates the uneven distribution of changes in R&D over time when the observation moves from an actual value to an imputed value and vice versa. The distribution of R&D growth rates is a smooth bell shaped curve only for those

[20]Until 2007, this publication was part of the MA14 Business Monitor.

observations which move from an actual value to another year's actual value.

Figure 11: Kernel density estimates for y-o-y real growth in R&D, size band 100-399



While aggregating from the reporting unit level to the enterprise level, it would not be consistent to add up an imputed value with a nonimputed value, hence we only aggregate the nonimputed values for each observation where available. For the enterprise-year observations which include an imputed value by one of the reporting units, the whole enterprise-year observation is considered as 'missing'.

A.3 Sector distribution of enterprises

Heterogeneities across treatment and control groups in terms of their sectoral compositions have been discussed in Section 3.4. Table 3 demonstrated that the change in sectoral compositions over time requires us to control for sectors in the estimation stage. More detailed evidence on this can be observed in Table 9, where the distribution of observations over two digit manufacturing sectors is presented. In the table, columns represent number of observations in a given sector, period (pre or post) and treatment or control group. The percentages show the share of observations in the sector for a given cell, where a cell can be one of the following: (i) control group pre-treatment, (ii) control group post-treatment, (iii) treatment group pre-treatment, and (iv) treatment group post-treatment.

Table 9: Distribution of observations across product groups

		TREATMENT GROUP				CONTROL GROUP			
	Own tech class	pre	%in total	post	%in total	pre	%in total	post	%in total
Pharmaceuticals	H	29	3%	15	2%	11	1%	36	5%
Office machinery	H	26	3%	18	3%	18	2%	15	2%
Radio, TV, comm.	H	74	7%	71	10%	64	8%	93	13%
Precision instruments	H	121	12%	64	9%	90	12%	82	11%
Refined petroleum	M	..	..	..	..	..	..	..	..
Chemicals	M	130	13%	75	11%	91	12%	90	12%
Machinery	M	166	16%	114	16%	145	19%	111	15%
Electrical machinery	M	90	9%	60	9%	60	8%	44	6%
Railway, rolling stock	M	..	..	..	..	..	..	..	..
Aircraft, spacecraft	M	16	2%	13	2%	..	..	..	..
Recycling	M	..	..	..	..	..	..	..	..
Food, beverages,	L	47	5%	52	7%	31	4%	35	5%
Textiles and clothes	L	36	4%	17	2%	24	3%	13	2%
Wood, paper,	L	19	2%	15	2%	20	3%	23	3%
Rubber and plastics	L	56	5%	44	6%	29	4%	38	5%
Nonmetallic minerals	L	29	3%	17	2%	20	3%	24	3%
Basic iron	L	..	..	..	..	..	..	..	..
Nonferrous metals	L	14	1%	20	3%	..	..	..	..
Fabricated metals	L	45	4%	23	3%	38	5%	29	4%
Motor vehicles	L	56	5%	40	6%	25	3%	32	4%
Shipbuilding	L	..	..	..	..	..	..	..	..
Furniture	L	29	3%	20	3%	33	4%	26	4%
Total		1021		704		756		737	

..disclosive

H: High tech, M: Medium tech, L: Low tech

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Chapter 2

Fiscal incentives in R&D intensive sectors: using corporation tax returns to evaluate the impact

(co-authored with Li Liu)

Abstract

Significant changes were introduced to the UK R&D tax incentive scheme in 2008, with the enhanced deduction rates rising for SMEs from 150 percent to 175 percent and for large firms from 125 to 130 percent. In addition, the SME definition was expanded to include some companies that were previously labeled as 'large'. For a company that for tax credit purposes moved from 'large' status to 'SME' because of this change, the reforms together meant up to a 27 percent reduction in the user cost of R&D capital, which is sizable. We estimate how qualifying R&D expenditure for the tax credits responds to changes in the R&D tax credit, by exploiting differential effects of R&D tax incentives on companies around the size threshold for eligibility to the SME scheme. We use difference-in-differences to estimate the effect of the policy reform and find that treated companies increased their R&D intensity by about 12 percentage points in response to the SME definition change.

JEL Classification: H25, O31, O38

Keywords: Tax incentives, corporation tax returns, quasi-experiment

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Contents

1 Introduction

Tax incentives are one of the main policy tools used by governments around the world to stimulate the level of business expenditure on research and development (R&D). This paper evaluates the effectiveness of fiscal incentives in R&D intensive sectors in the United Kingdom. First introduced in the UK in the period 2000-2002, tax incentives for R&D in the UK have become increasingly generous. However, a rigorous evaluation of the efficacy of the R&D tax incentives has proven difficult, partly due to the lack of suitable microdata and partly due to the lack of a compelling identification strategy.

This paper aims to identify the causal effect of tax incentives on R&D investment using the population of corporation tax records that provide precise information on the amount of firm-level R&D expenditure that qualify for the tax incentive. Using the corporation tax records allows us to identify for each R&D active company the precise tax positions (for example, whether they have any taxable profits) and the corresponding rate of deduction for qualifying R&D expenditure against the taxable profit, enabling us to measure the variation in the R&D tax credit. By linking the tax record to the financial statement for each company and year, we observe in addition other contemporaneous, non-tax determinants of R&D investment such as firm age, profitability and growth rate, which allows us to disentangle the true effect of the credit from other confounding factors.

Significant changes were introduced to the UK R&D tax incentive scheme in 2008-09, which resulted in differential changes in the R&D user cost of capital faced by small and medium sized (SMEs) companies compared to large companies. Specifically, the 2008 tax reform increased the enhanced deduction rate from 150 to 175 percent for SMEs and from 125 to 130 percent for large companies. More importantly, the reform expanded the SME definition by doubling the thresholds measured in employment size, turnover and total assets. As a result, a number of companies that would have been classified as large companies under the old system became qualified as SMEs. In the same year, the statutory corporation tax rate on small profits increased by one percentage point to 21 percent, whereas the main rate dropped from 30 percent to 28 percent. Incorporating all these changes, for a company that moved from large to SME status because of this change, we estimate that the overall effect of the reform amounts to a 29 percent reduction in the user cost of R&D capital. By comparison, the reform brought relatively little change in the user cost of R&D capital for companies that remained as SMEs or remained as large companies.

Exploiting the differential change in the R&D tax incentives as identifying variation, we estimate the causal effect of the tax credit on qualifying R&D expenditure using a difference-in-difference (diff-in-diff) approach. Firms in the treatment group comprise those newly-defined SMEs as a result of the 2008 reform, and firms in the two alternative control groups consist of SMEs that are slightly below the old threshold and large companies that are slightly above the new threshold. For the diff-in-diff approach to be consistent, it must hold that other differences between treated and control companies are not systematically related to changes in R&D investment over the treatment period. While this assumption cannot be directly tested, we show that there are no significant trend differences in R&D investment between treated and control companies in the pre-2008 period.

With the approach described above, we find that the treated companies on average increased the R&D intensity by around 12 percentage points in response to the increased tax incentive generosity in 2008. The positive and significant effect of R&D tax incentive is robust to the use of alternative control groups, to the inclusion of controls for non-tax determinants of R&D investment, as well as to varying the time period to control for any potential anticipation effect. This robust evidence supports the effectiveness of tax incentives on the intensive margin of R&D investment. We further examine extensive-margin adjustments of R&D investment and find no evidence that this reform encouraged firms to undertake R&D investment if they had not done so before. In addition, we examine the response of wages to tax incentives and find no significant effect of the reform on total wages and salaries in companies engaging in R&D.

The remainder of the paper is structured as follows. Section 2 describes in detail the deduction rates and the SME definition change that were introduced in the 2008 tax reform. Section 3 describes the data sources and summarizes the dataset used for the analysis. Section 4 explains the research design and reports the main results as well as several robustness checks. Section 5 discusses the main findings. Section 6 concludes.

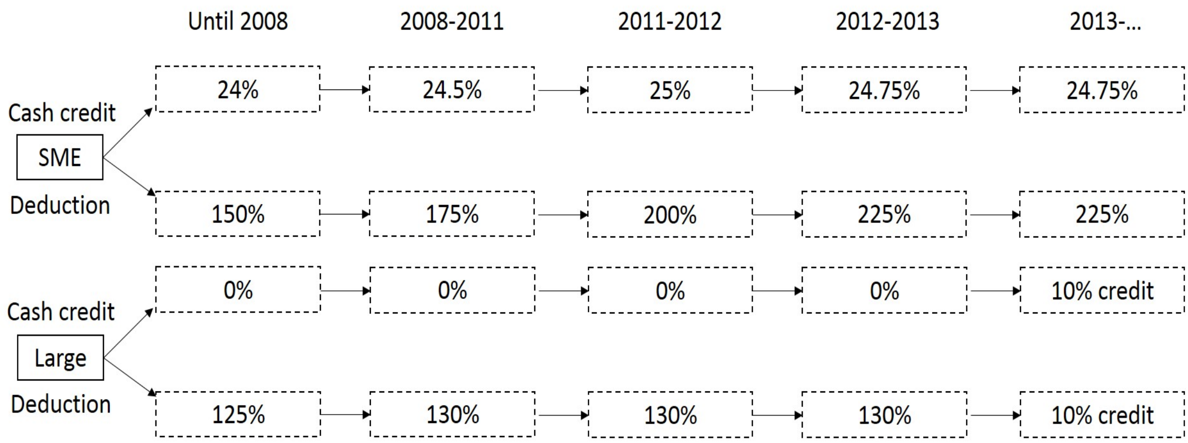
2 Policy background

The UK introduced R&D tax incentive schemes in 2000 for SMEs and in 2002 for large companies. Since its introduction, the R&D tax incentive scheme has become more generous for both SMEs and large companies, following a pledge from the Government to increase business R&D documented in a number of official documents, including the 2007 and 2008 Pre-Budget and Budget reports. The UK R&D tax relief started in 2000 in the form of an enhanced deduction for SMEs, then got expanded in 2002 to also support R&D by larger companies at a lower rate. Until the changes studied in this paper, the SME scheme allowed companies to tax deduct £150 for every £100 spent on qualifying expenditures on R&D and the large company scheme allowed a deduction of £125 for every £100. A cash credit was (and still is) available for SMEs which are in a loss-making position and the amount of cash paid to such SMEs amounted up to 16 percent of the total surrenderable loss of the claimant (see Appendix A for the details on cash benefits for SMEs). In April 2008, the large company deduction rate increased from 125 percent to 130 percent and the SME deduction rate increased from 150 percent to 175 percent. The cash credit rates for SMEs were adjusted to keep the cash benefits at a maximum of 24-24.5 percent of total R&D spending by the company. The treatment of subcontracted R&D remained the same and required that the R&D carried out by an SME which operates under a subcontracting relationship with a large company can only benefit from the large company scheme, which features a lower deduction rate and a lower cash credit rate.

The transition from the Labour Government to the Conservative-Liberal Democrat Coalition Government after the 2010 general elections did not change the R&D

policy substantially; the new Government continued to support the R&D agenda and strengthened its commitment to increasing business R&D through tax incentives. In 2011, further changes were announced to the SME scheme, increasing the deduction rate further 200 to percent in 2011 and to 225 percent in 2012. From 2013 onwards, an optional tax credit, which is directly deducted from the final tax liability of companies and is itself taxable, was introduced for large companies at a rate equivalent to the enhanced deduction rates (a taxable credit rate amounting to 10 percent of R&D expenditure). It was also announced that the large company scheme would completely switch to an above-the-line taxable credit from April 2016 onwards. Figure 1 summarizes the changes in rates starting in 2008.

Figure 1: Evolution of R&D tax relief deduction rates



The tax price of R&D was not only affected by the R&D tax incentive over the period of interest for this study. A gradual change in the corporation tax rates also took place in the last decade. Between 2002 and 2006, the main rate for corporation tax was 30 percent, and the small profits rate, which applied to companies with taxable profit less than £300,000, was 19 percent[1]. In the 2006-07 financial period, the small profits rate increased to 20 percent, and then to 21 percent in 2007-08. From 2011-12 onwards, the small profits rate has been maintained at 20 percent. The main rate has

[1]Between 2000 and 2005, there was also the ‘starting rate’ rule, which allowed initially a 0 percent rate on companies with taxable profits less than £10,000. This rate was then increased to 10 percent until the end of the scheme in 2005. For taxable profits between £300,000 and £1.5 million, marginal tax relief fractions apply.

gradually been dropping. In 2007-08, the main rate dropped from 30 percent to 28 percent, and then in 2011-12, to 26 percent, followed by further annual drops to 24 percent, then to 23 percent, finally reaching 21 percent in 2014-15.

While the rate changes in the R&D tax incentive and corporation tax alter the tax price of R&D spending, the most dramatic reduction in the cost of marginal R&D investment for a group of firms was introduced in the August 2008 reform, which changed the definition of a small or medium sized enterprise (SME) used to determine eligibility for the more generous tax treatment of R&D by doubling all the thresholds for defining an SME. Other types of tax allowances for SMEs apart from the R&D tax relief were not affected by this definition change. These thresholds are presented in Figure 2. Specifically, before the reform, a UK company was defined as an SME if (i) it has fewer than 250 employees, and (ii) its total asset size is less than €43 million or its annual turnover is less than €50 million. After the reform, a UK company is defined as an SME if (i) it has fewer than 500 employees, and (ii) its total asset size is less than €86 million or its annual turnover is less than €100 million. As a result, there was a range of companies that became qualified as SMEs but would have been classed as large companies under the old thresholds. Thus in 2008, the SME R&D tax incentive scheme became more generous, and covered all the newly-defined SMEs. Combining the effect of both the rate increases and the SME definition change, an SME that was previously labeled as 'large' before the reform could deduct, for every £100 of qualifying R&D, £125 against its taxable profit in financial year 2007-08 and £175 in 2009-10. Given that the eligibility thresholds reform took place in mid 2008-09, the amount of R&D performed in 2008-09 was apportioned as follows: the amount of R&D spent prior to 1 August 2008 was subjected to the revised large company rate of 130 percent, and the amount spent on or after 1 August 2008 was subjected to the revised SME rate of 175 percent[2]. Newly-qualified SMEs also became eligible to claim cash if they incur zero or negative taxable profits in the current financial year. Details of cash benefits are explained in Appendix A.

[2]HMRC asks that the companies make a distinction between expenditure incurred before and after 1 August 2008 in calculating the total enhanced spending on R&D in the calculation of the corporation tax liability for the accounting period which includes 1 August 2008.

Figure 2: Size thresholds for SME tax credit

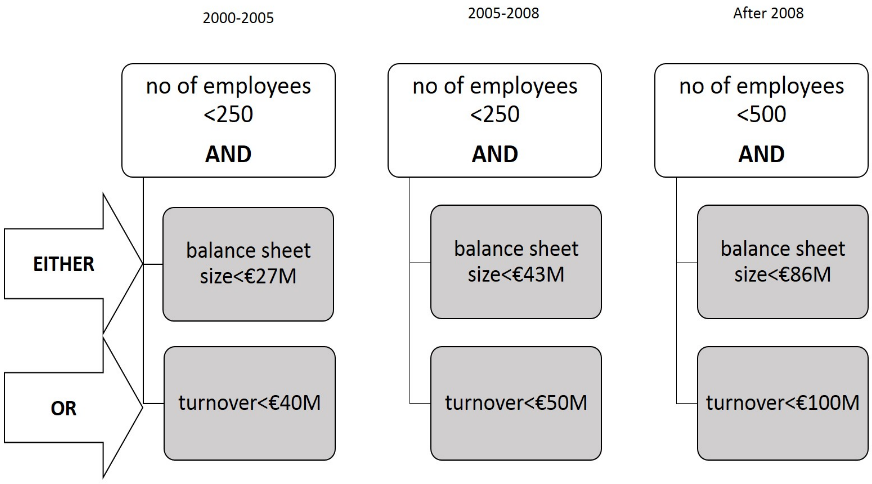


Figure 2 shows an earlier SME definition change in 2005, included for the purpose of completeness, which only affects the balance sheet and turnover thresholds. Unlike the 2008 reform, the 2005 definition change applied to other tax allowances and benefits for SMEs in addition to the R&D tax breaks, since it was a result of an EU-wide definition change. As can be observed in the figure, the binding criterion to define an SME for the purpose of the R&D tax incentive is the employment criterion, and the changes in the balance sheet size and turnover criteria in 2005 have been small, unlikely to generate any behavioral changes in R&D spending. For these reasons, we did not consider the 2005 definition change as a separate policy experiment.

In the Budget Report of 2006, the Government declared its intention to "...extend additional R&D tax credit support to companies with 250-500 employees, subject to the outcome of the state aids discussions with the European Commission. (HM Treasury Budget Report, 2008, Article 3.80)"[3].

This study aims to identify the causal effect of tax incentives on (qualifying) private R&D by exploiting the 2008 SME definition change that applied only to companies with 250-500 employees prior to the reform; such companies form a natural treatment group that experienced an exogenous drop in their tax price of R&D. By comparison, companies that continued to be SMEs or large companies were unaffected by the

[3] It was therefore clear to companies with 250-500 employees then that this reform was very likely to take place even two years prior to its implementation. We discuss implications of any such anticipation effects in details in Section 4.1.

change in R&D tax incentives that were introduced by this particular reform. Close to the introduction of this SME definition change, concurrent changes in the R&D tax incentives took place, as discussed earlier, which includes the increased deduction rates for both SMEs and large companies. For this reason, around the time of implementation of this eligibility reform, holding all non-tax related variables constant, we would expect part of the effect of tax policy on R&D spending of the treated firms to arise from the increased deduction rates and part of it from the SME definition change.

There were also changes to marginal corporate tax rates during this period. The main statutory tax rate dropped from 30 percent to 28 percent for companies with taxable profits over £1.5 million in 2008-09, while the small profits rate increased from 19 percent to 20 percent in 2007-08 and further increased to 21 percent in 2008-09 for companies with taxable profits below £300,000[4]. A lower statutory tax rate also decreases the value of the deductions, and we capture all these changes in the user cost of R&D capital.

Against the backdrop of all these tax-related reforms, the tax component of the user cost of R&D stock [5] evolved as depicted in Figure 3. The figure shows the changes in the tax component of the user cost for different tax rate brackets and R&D relief rates. Tax component of the user cost is calculated as $\frac{1-A}{1-\tau}$, where A is the value of tax credits and depreciation allowances for £1 spending in R&D and τ is the statutory tax rate. This formulation suggests that the value of tax credits and allowances A be obtained by multiplying $1+d$, where d is the deduction rate, by the statutory tax rate (for example, $A = (1+0.5)\tau$ for an SME in the pre-2008 period). The eligibility rules for tax payments at the 'small profits rate' as opposed to the 'main rate' are separate from the eligibility rules for the more generous R&D tax incentives for SMEs. The distinction between eligibility for the main rate or the small profits rate for corporation

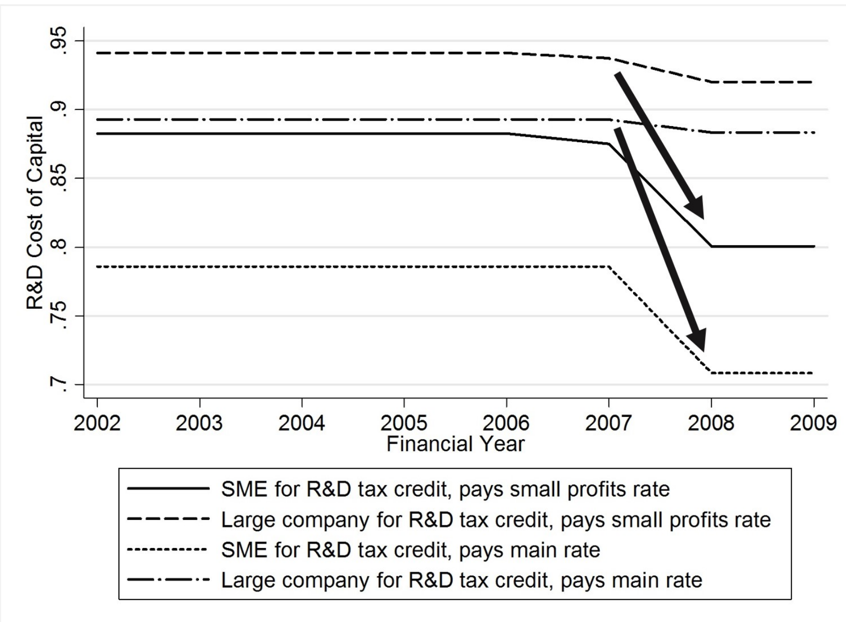
[4]Taxable profits between £300,000 and £1.5 million are subject to 'marginal tax relief fractions', which allows companies in this tax bracket to claim relief by a fraction defined by HMRC on the amount by which the company undercuts the £1.5 million threshold. These marginal tax rate fractions have also been changing over the period of interest for this study, as they are adjusted according to the rate changes. In 2007-08, this fraction was 10/400, which dropped to 7/400 in 2008-09.

[5]Figure 3 accounts for the change in the user cost for 'current spending' on R&D, which covers researchers' salaries, materials and supplies. As discussed in Chapter 1 of this thesis, on average, around 90 percent of firm-level R&D expenditures are current spending. There has been no change in the treatment of capital expenditures in R&D during the period studied.

tax payments applies to all the companies, independent of whether they perform R&D or not, and the rate applicable to a certain company depends on its taxable profits. On the other hand, the eligibility criteria for the more generous R&D tax relief for SMEs depends on firm characteristics as explained before, and it is not dependent on the amount of their taxable profits.

In Figure 3, a representative company that is eligible throughout the period for the R&D tax relief for SMEs experiences a drop in its user cost due to the increase in the deduction rate from 150 percent to 175 percent. The increase in the deduction rate from 125 to 130 percent for large companies is partly offset by the decrease in the main statutory tax rate. The arrows indicate the transition for a company that was labeled as 'large' before the SME definition change and as 'SME' after this reform. A representative company that benefited from the definition change experienced a decrease in the R&D user cost by around 21 percent between 2007 and 2009 if paying at the small profits rate, and around 15 percent if paying at the main rate.

Figure 3: Tax component of the user cost of R&D on current spending



3 Data

3.1 Description of the data sets

We linked two data sets to create the panel used in this study: (i) the universe of UK corporation tax assessments from the HM Revenue and Customs (CT600); (ii) annual company accounts from Bureau van Dijk's Financial Analysis Made Easy (FAME) Database.

The CT600 data set includes the population of company tax records and provides information on the precise tax position of a company including its taxable profit, loss brought forward, trading profit and losses, turnover, the amount of R&D tax deductions and cash credits claimed for the periods under study, whether the company claimed under the SME scheme or the large company scheme, and the total amount of subcontracted R&D for an SME company claiming as a subcontractor under the large company scheme. However, information on which R&D tax incentive was claimed is missing for around 20 percent of companies with qualifying R&D, since they report a positive enhanced deduction for R&D but did not fill the CT600 Boxes for SME (Box 99) or Large (Box 100) company[6]. We use two approaches to address this group of companies with missing size indicator. The first approach excludes these observations from the analysis altogether and thus ignores potentially useful information provided by these companies. Alternatively, we rely on complementary accounting information from FAME on the number of employees and total assets to predict whether a company qualifies as an SME following the definition thresholds set out in Figure 2. The overlap between these two approaches is discussed later in this section and in Appendix B, where it has been shown that using the information on employment and total assets from FAME is not successful in identifying the companies classified as large for the purpose of the R&D tax relief. There is also not a substantial shift in the degree of overlap between the CT600 identifier variable and the information gathered using FAME around the time when the eligibility thresholds doubled.

[6]One of the reasons for this has been reported as the fact that the information from HMRC's R&D Compliance Units is missing in the data set.

More than 90 percent of the tax records are matched with company accounts in FAME. The CT600 data currently covers the financial years from 2000-01 until 2009-10[7]. Combining information on enhanced R&D expenditure, total amount of subcontracted R&D and whether the company is SME or large, we are able to infer the total qualifying R&D spending of each company in a given year. Specifically, we scale down the total annual R&D enhanced expenditure for a company by the deduction rate in the corresponding year. For example, an SME that reports £30,000 of enhanced deduction and £25,000 of SME claim under the large company scheme as sub-contractor before the 2008 rate changes must have undertaken a total qualifying R&D of £30,000∗(100/150)+£25,000∗(100/125) =£40,000.

Table 1 presents an overview of the number of observations in CT600 with non-missing R&D information, which comprises the universe of companies with qualifying R&D expenditure over the sample period. In each financial year, we compare the number of observations with a positive R&D enhanced deduction, the number of SME sub-contractors, the number of observations with positive repayable credit, and the total number of observations that checked Box 99 and Box 100 for SME and large company claims, respectively. The size of the qualifying R&D sample in the UK has gradually increased over the sample period, as indicated by the increasing number of observations in each column. Over the same period, the share of claimants of the R&D tax relief in total corporation taxpayers increased from around 0.4 percent to 0.9 percent, meaning that the number of R&D tax relief claimants increased more than proportionately. In Table 1, the discrepancy between the first and final columns is due to the group of companies with missing size indicators since we were unable to calculate the total qualifying R&D using the CT600 data without knowing the precise deduction rate. There are also cases where the size indicator is available, but the enhanced R&D amount is missing, although these cases are less frequent than the opposite. It appears that the cases with missing information on enhanced deductions dominate only in 2002-03.

[7] At the time of drafting of this chapter, the HMRC teams have been working on an updated version of CT600 to cover an additional two years.

Table 1: Number of observations in CT600 with R&D information

FY	Enhanced deduction (I)	SME subcontractor (II)	Repayable credit (III)	SME flag (Box 99) (IV)	Large flag (Box 100) (V)	(IV)+(V)
2001-02	2063	..	939	203	..	..
2002-03	3381	80	1270	3690	391	4081
2003-04	4004	108	1281	3160	592	3752
2004-05	4354	157	1241	2863	699	3562
2005-06	4478	221	1203	2858	775	3633
2006-07	4954	260	1237	3206	849	4055
2007-08	5801	270	1374	3660	1040	4700
2008-09	6780	329	1545	4244	1177	5421
2009-10	7931	384	1629	4778	1216	5994

We complement the CT600 data with additional firm characteristics in FAME and construct an alternative SME flag using information from the employment, turnover and total asset variables. We then check the quality of the FAME SME/large indicator by comparing with the CT600 size indicator. It is crucial to define the SME status of a company accurately in each year, as we rely on this information to define the treatment group as companies that switched from large to SME in the year of implementation of the reform. While we leave the detailed explanation of the construction of this variable and its overlap with the CT600 indicators to Appendix B, it is important to note that the success rate of the FAME indicator in labeling a company that ticked Box 99 (SME) is around 97 percent, while the success rate of the FAME indicator in predicting a company that ticked Box 100 (large) as large is much lower and around 43 percent. One potential explanation for the low success rate of FAME indicator in predicting large company status is that SMEs which belong to a larger company group are classified as large companies for the purpose of the R&D tax incentive scheme. Currently there is no precise information on firm ownership in the linked CT600-FAME dataset used in this study, so that we cannot re-classify firms which appear to be SMEs in our FAME data but which have large parent companies in the same way. We thus focus the presentation here on the sub-sample with SME or large company status recorded in the CT600 data, and we outline the methodology for using the alternative FAME indicator in Appendix B.

3.2 Qualifying R&D and total BERD

Chapter 1 of this thesis discussed the trends in UK's performance in Business Enterprise Research and Development (BERD) and it has been demonstrated that the overall BERD intensity measured as the share of total BERD in total value added in the UK has been on a slightly declining trend in the last 25 years. Over the period 2001-2009, the BERD intensity has been roughly stable, at a ratio of around 1.2-1.4 percent. Chapter 1 also underlined the role of the structural transformation in the UK economy from manufacturing towards services in the last three decades, showing that the modest performance of aggregate BERD intensity may be partly attributable to this shift, since the R&D intensity in high technology manufacturing sectors was on the rise, however, the share of manufacturing in total value added declined substantially.

Using the CT600 data set has the advantage of providing information on the universe of the actual claimants of tax incentives rather than the intent to treat, which is a prediction by the researcher that has to ignore the issue of take up. On the other hand, a drawback of the CT600 data set is that it provides no information on R&D spending that does not qualify for the tax relief. In an evaluation of the UK R&D tax relief schemes, the ideal scenario would be to merge the BERD data from ONS sources (used in Chapter 1) with the CT600 data set used in this chapter and to consider the interactions between qualifying and non-qualifying R&D expenditure, but this is not possible as currently ONS and HMRC data cannot be linked[8].

The HM Revenue and Customs Corporate Intangibles and R&D (CIRD) Manual identifies three main categories of qualifying expenditures for the purpose of the R&D tax relief. These include staffing costs, consumables (such as water and electricity) and software directly used in R&D, and subcontracted R&D. Additionally, contributions by the companies to research undertaken at independent research institutions (academic or other research institutions which are not connected to the firm) qualify under the large company scheme if they are relevant for the company's main activity. By definition, qualifying expenditures exclude any spending that is only indirectly related to the R&D

[8] Naturally, any R&D carried out before the introduction of the R&D tax relief is not observed in the CT600 data.

activity of the firm.

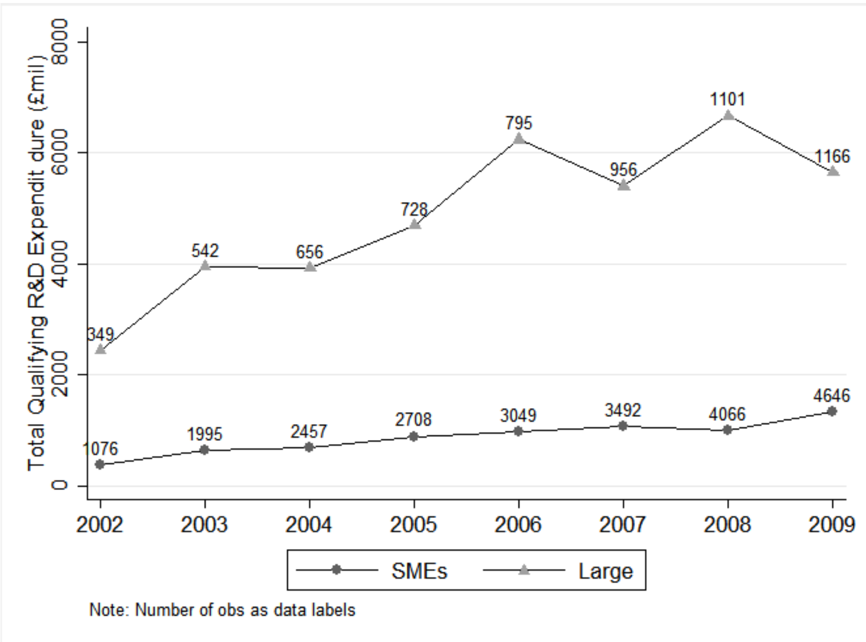
We complement the CT600 size indicator with the FAME size indicator for companies with missing CT600 size indicator to compute the aggregate qualifying R&D expenditure in CT600. Ignoring information on R&D expenditure provided by this group of companies would result in underestimation of the total qualifying R&D. Specifically, for companies with positive R&D deduction and missing Box 99 and Box 100 information, we use the FAME data to identify their size category. At firm level, annual qualifying R&D is calculated by scaling the enhanced R&D value to the expenditure on which the claim has been made.

According to the ONS estimates, the total current R&D spending by all UK businesses amounted to around £12.5 billion in 2005, which increased to around £14.5 billion in 2009 (in nominal terms). The ratio of total qualifying R&D spending that is observed in HMRC data to the aggregate current spending in BERD published by the ONS has been around 50 percent over the period in which HMRC data can be observed. Several potential explanations for this relatively small ratio include, but are not limited to: (i) R&D spending in the non-corporate sector, (ii) low take up by eligible firms which are not claiming and observed in the CT600 data, (iii) R&D spending that are not qualified for relief, and (iv) missing information on R&D expenditure from HMRC's R&D Compliance Units that are not included in the CT600 data[9]. Regarding this final point, the discrepancy is observed when the micro data totals on the number of claims as presented in the final column of Table 1 are compared with the published statistics from HMRC, which indicate that the micro data totals of SME and large company claims remain at around 60-65 percent of the published statistics (without a change over time in this ratio). The number of enhanced deductions and SME subcontractor claims, on the other hand, are very close to the published aggregates, suggesting that the missing information in CT600 from R&D Compliance Units may be an important factor in explaining part of the differential between total BERD and total qualifying R&D.

[9] HMRC is in the process of making this information available for analysis at the time of drafting of this thesis chapter.

Figure 4 demonstrates that the total qualifying R&D has risen steadily over time until 2006-07, followed by a drop in 2007-08 and then continuing to rise in 2008-09. The drop in 2009-10 may be attributable to the liquidity constraints driven by the global recession or alternatively, could be due to delay in tax filings and R&D tax incentive claims since it is the last year of the sample period, although there is no support for this alternative explanation in Table 1. The drop in 2007-08 is more likely to be driven by the anticipation effect, since the announcement of the rate increase in the forthcoming year may have caused a postponement of the qualifying R&D spending to the subsequent period. In Section 4, we discuss such effects in detail and remove the periods between announcement and implementation of the policy in the regressions.

Figure 4: Trends in total qualifying R&D expenditure, in real (2008) £million



3.3 Definition of treatment and control groups

We use two approaches to define the treatment and control groups, depending on whether we utilize additional information from FAME to determine company size. First, we use the information in Box 99 and Box 100 only to identify SMEs and large companies which benefit from the R&D tax relief. Given its SME or large company status, a company is defined as 'treated' if it carried out qualifying R&D or subcontracted work in either 2008 or 2009, is labeled as SME in at least one of these two years, and further satisfies one of the following conditions: (i) labeled large and performed R&D in 2006 and/or 2007, or (ii) labeled large and performed R&D in 2005 if it did not have any R&D operation in 2006 or 2007, or (iii) labeled large and performed R&D in 2004 if it did not have any R&D operation in the following three years, or (iv) labeled large and performed R&D in 2003, which is the last year for which the company undertook some positive R&D investment before the 2008 reform.

Following a similar approach, we construct a control group of large companies and a control group of SMEs. By further restricting companies in these two groups based on employment size bands, we construct two control groups with more similar firm characteristics to those in the treatment group. Specifically, a company is included in the SME (large) control group if it carried out qualifying R&D or subcontracted work in either 2008 or 2009, and is labeled 'SME' ('large') in at least one of the two years, and satisfies one of the following: (i) either labeled SME (large) in 2006 and/or 2007 and performed R&D in that year, or (ii) labeled SME (large) and performed R&D in 2005 and did not have any R&D operation in 2006 or 2007, or (iii) labeled SME (large) and performed R&D in 2004 and did not have any R&D operation in 2005, 2006 or 2007, or (iv) labeled SME (large) and performed R&D in 2003 and did not have any R&D operation in the following years, or (v) labeled SME (large) and performed R&D in 2002 and did not have any R&D operation in any of the later pre-reform years.

To ensure that the control groups include companies similar in non R&D characteristics with those in the treatment group, we refine the definition of control groups based on their employment size: a narrower SME control group including companies with at least 100 employees, and a narrower large control group including companies with at most 750 employees in all periods during which the employment variable is available. We further check the robustness of our findings to the arbitrary cutoff points at 100 and 750-employee thresholds; experimenting with wider or narrower employment size bands based on the distribution of employment in treated or control groups makes little difference in the magnitude or the significance of the results presented later in the paper.

The second approach follows the same principles in defining the treatment and control groups, except that it complements companies with missing CT600 size indicators with information from FAME. This increases the number of treated companies from around 55 to around 130 in a given year.

3.4 Descriptive statistics

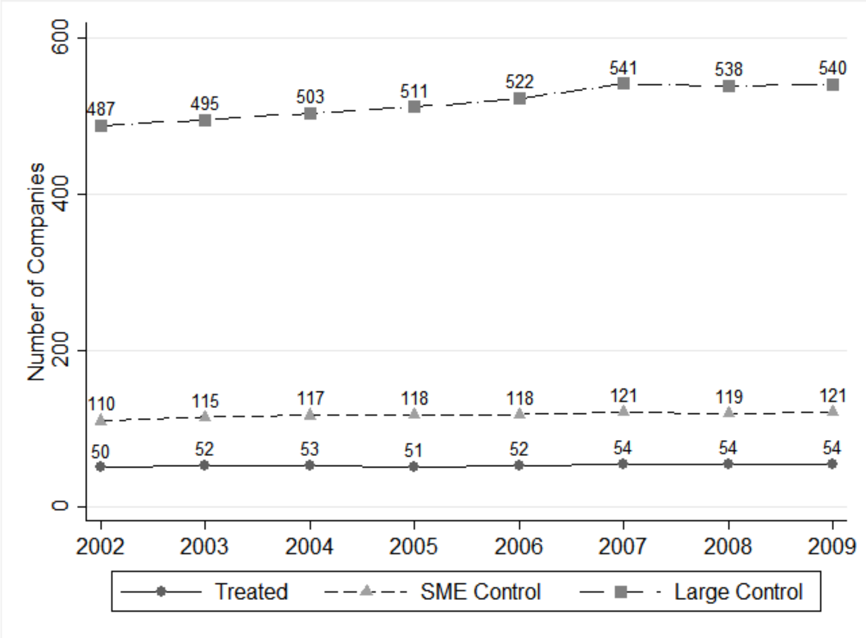
Based on the treatment definition utilizing the CT600 data only, around 55 firms per year fall in the treatment group. This is a small number of companies, but all of these companies are observed at least once before and once after the reform with most of them observed in all years during the sample period. We construct two samples by including the treatment group and the SME or large control group, respectively. Each sample, for which the descriptive statistics in this section and the results presented in Section 4 are obtained, includes all the treated observations and either the large control group with companies with up to 750 employees (Sample Large-750), or the SME control group with companies with at least 100 employees (Sample SME-100). In Section 4, we also report results based on a larger SME control group which does not exclude SMEs with less than 100 employees. For brevity we do not report the descriptive statistics for this latter sample in this section.

The number of observations in the treatment, SME and large control groups is presented in Figure 5. Refining control groups based on employment size bands gets the number of observations and firm characteristics in the control groups closer to the treatment group, but both control groups continue to have a considerably larger number of observations. In Sample SME-100, there are up to 120 companies in each year in the SME control group, and about 500 companies in the large control group in Sample Large-750 throughout the sample period.[10]

The broad sectoral distribution of companies is very similar across treated and control groups, with 50 to 60 percent of the companies in manufacturing sectors. This

[10]Narrowing down this latter control group does not alter the average values of firm characteristics reported in Tables 2 and 3 and the general aspects discussed below carry over to smaller sized control groups composed of firms with more than 500 employees.

Figure 5: Number of observations across treatment and control groups



share is slightly higher in the SME control group, where 60 percent of firms operate in manufacturing[11]. In the treatment and control groups of interest, the majority of companies in the service sector belong to the two-digit SIC (2003) categories of either ‘research and development (73)’ or ‘computer and related activities (72)’. Companies in these service sector categories mainly engage in research and development and produce intellectual property or contractual arrangements with other companies that purchase their R&D services as final outputs. The nature of service companies differ substantially from production firms which produce manufactured products as final outputs. In particular, we may expect an R&D intensity measure such as total R&D as a share of the companies’ sales to be much larger in the service sector relative to manufacturing. By construction, the sectoral composition of treatment and control groups remained stable around the 2008 reform, ensuring that none of the identified policy effect is driven by sectoral shifts between the manufacturing and service sectors.

Table 2 presents average firm characteristics by treatment and control groups. As expected, the average sales and profit are higher in the large control group.

Throughout the observed period, the large control group experienced a steady up-

[11]Note that since we do not have any information on the breakdown of these companies’ fields of research and development activity, we can comment only on the sector of their final product.

ward trend in R&D intensity, while the treatment group and the SME control groups demonstrate some fluctuation. On average, the treatment group also experienced an upward trend in R&D intensity, and this metric for the SME control group remained roughly stable. Later, we show that the median R&D intensities increased for all the three groups between 2005 and 2009, with the treatment and SME control groups experiencing a temporary drop in 2008 (Figure 8).

The summary statistics in Tables 2 and 3 treat each company that is a corporate taxpaying unit individually, and do not take into account ownership relations between these companies which may affect their characteristics such as employment size, sales and total assets for the purpose of determining their eligibility for the different types of R&D tax relief. Possibly because of this caveat, we observe smaller average firm size values in each of the SME control, treatment and large control groups than the threshold values of 250 and 500 employees, which we would at least expect the treatment and large control groups to reach on average. Over the sample period, the average employment is around 190 for the large control group, around 170 for the SME control group and around 160 for the treatment group. Company size measured by employment drops for all the three groups in 2009, which is expected as a result of the recession that began in the third quarter of 2008. Median employment values, which are not shown in the tables, are also around the same ballpark figures reported for the means, suggesting that the small employment numbers in treatment and large control groups are not attributable to outliers in the tables.

Firm size measured by total assets of the firm does not appear to be as dramatically affected by the recession as the average employment numbers, with a stable level of average asset size around £12 million for the treated and SME control groups and around £55 million for the large control group.

Table 2: Means of key variables across groups (I), values in real (2008) '000 GBP

	Sales			Trading Profit/Loss		
FY	Treat	SME Cont	Large Cont	Treat	SME Cont	Large Cont
2002-03	14,063	14,516	32,401	345	113	1,644
2003-04	16,707	14,458	34,603	334	258	1,958
2004-05	13,215	15,162	38,107	183	228	442
2005-06	14,642	15,541	39,770	553	232	2,927
2006-07	15,443	16,185	41,985	529	223	2,486
2007-08	16,574	16,253	45,839	417	-172	3,603
2008-09	16,249	17,370	50,071	410	198	4,842
2009-10	14,194	16,393	46,903	415	410	3,387

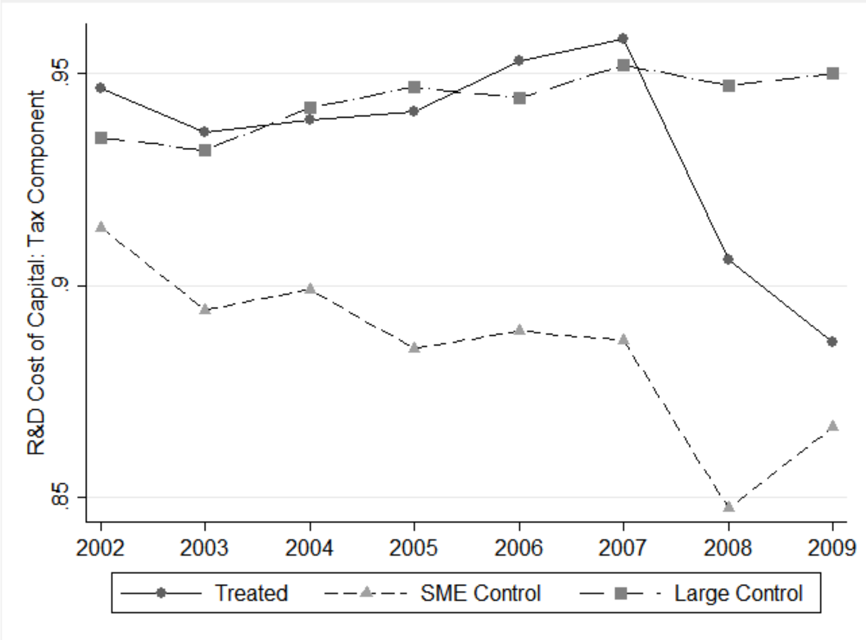
Table 3: Means of key variables across groups (II), values in real (2008) '000 GBP

	R&D Intensity			Assets			Employment		
FY	Treat	SME Cont	Large Cont	Treat	SME Cont	Large Cont	Treat	SME Cont	Large Cont
2002-03	0.5%	0.6%	4.2%	10,290	11,907	38,176	177	176	188
2003-04	2.8%	6.8%	4.9%	9,638	11,592	41,417	155	173	189
2004-05	3.6%	4.9%	7.9%	10,042	11,774	43,267	162	169	193
2005-06	11.9%	3.5%	8.7%	11,483	12,346	46,837	154	169	191
2006-07	5.6%	4.3%	8.7%	11,885	12,853	48,674	171	171	192
2007-08	13.3%	4.7%	8.7%	12,943	13,246	52,638	168	171	198
2008-09	6.6%	4.7%	9.6%	13,255	13,801	56,133	166	174	204
2009-10	23.5%	4.0%	10.6%	13,067	13,382	54,900	147	166	195

If many firms are in a loss-making position, or if they are in different tax brackets, then the value of the enhanced deduction may vary considerably, and this could mask the identifying variation in the user cost generated by the policy reform. To rule out this possibility, we calculate for each company-year observation a measure of the user cost of R&D capital to assess whether variation in the tax component of the user cost of capital indeed resembles the pattern depicted in Figure 3. Calculation of the user cost of R&D capital here is based on simple assumptions mainly following Bloom et al. (2002), with a fixed real interest rate of 5 percent and a depreciation rate of R&D capital (obsolescence) assumed to be 30 percent. The R&D user cost has been formulated as $u = \frac{1-A}{1-\tau}(r + \delta)$, where r and δ represent the assumed real interest rate and the depreciation rate for R&D capital respectively, and the first term $\frac{1-A}{1-\tau}$ is the tax component. $A = (1 + d)\tau$, where τ stands for the marginal statutory tax rate that applies to the company's profit bracket, d is the deduction rate and depends on whether the company benefits from the SME or the large company tax relief. For companies that are in a loss-making position in a given period, τ is assumed to be zero. These assumptions are made as an approximation for demonstration purposes and more refined estimates for the cost of capital should be obtained if the intention is to estimate a structural R&D investment model. Figure 6 shows that the calculated average user cost of capital indeed follows the pattern envisaged earlier in Figure 3 about the identifying variation in the tax component of the user cost triggered by the eligibility reforms in 2008. On average, treated firms experience a decline in their tax component of the cost of capital from 0.958 in 2007-08 to 0.887 in 2009-10, whereas the large control group remain at around 0.950, and the SME control group experience a more modest drop from 0.887 to 0.867 over the same period.

The patterns in firm characteristics shown in Table 2 suggest that the overall characteristics of the treated group and the SME control group are very similar to each other, whereas from the perspective of assessing the policy impact, the large control group appears to be a more suitable benchmark given the stable user cost of capital between pre- and post-reform periods for the firms that belong to this group.

Figure 6: Average user cost of capital across treatment and control groups, tax component

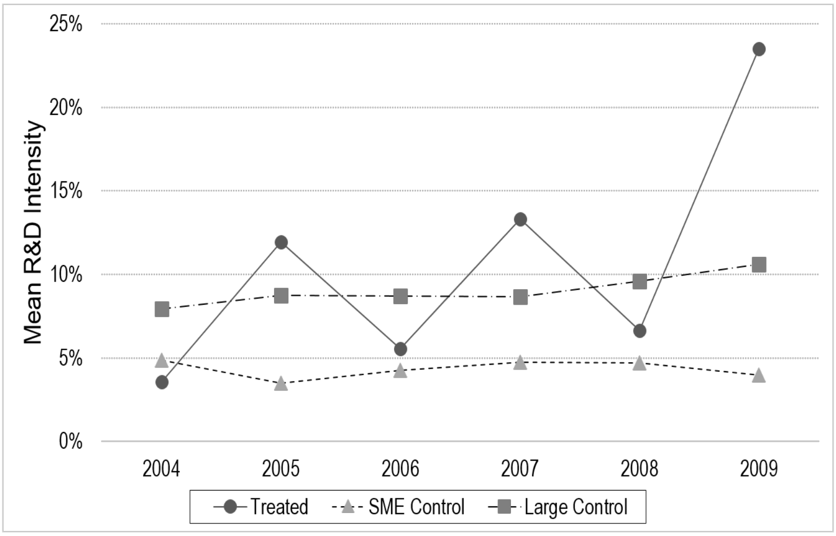


4 Results

4.1 Methodology

To identify the causal effect of the 2008 tax reform on R&D spending, we use a difference-in-differences (diff-in-diff) methodology. Diff-in-diff examines the average differential effect of the reform on R&D spending by the treatment group relative to the control group. The validity of the diff-in-diff approach relies on the common trends assumption which requires that, in the absence of treatment, the treatment and control groups would have experienced the same change in the outcome variable between the pre-treatment and post-treatment periods. We test this assumption by examining the pre-reform trends in the R&D spending in the treatment and control groups. Figure 7 shows the trends in the average R&D intensity in treatment, large control (with up to 750 employees) and SME control groups (with more than 100 employees), where R&D intensity for each company-year observation is computed as the qualifying R&D spending as a share of total turnover. On average, the pre-reform means tracks each other roughly in the treated and large control groups, with some fluctuation observed

Figure 7: Average R&D intensity across treatment and control groups



in the average R&D intensity in the treated group. The high volatility of the R&D intensity in the treated group is likely due to the small sample size, but this does not represent a violation of the common trends assumption.

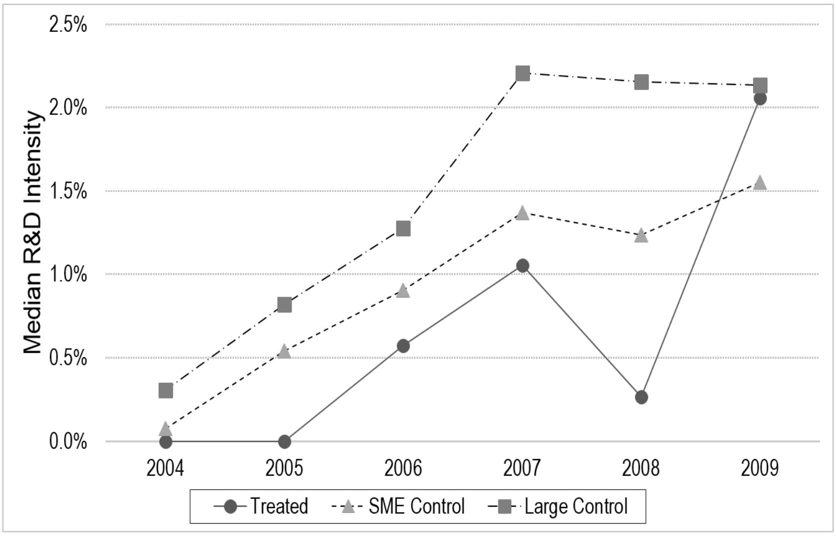
To verify that the differential increase in the treated groups' average R&D intensity is not driven by outliers, we also present the evolution of median R&D intensity for the period of interest in Figure 8. We observe that each of the three groups start at very low median R&D intensities, growing roughly in parallel between 2005 and 2007. Both the treatment group and the SME control group experience a drop in 2008, followed by increases in the median R&D intensity in 2009, whereas the large control group has a relatively stable median R&D intensity between 2007 and 2009.

The set up in the study appears to be an ideal one to apply a regression discontinuity design with multiple thresholds, or using only the employment threshold as the running variable to determine the effect of the policy by non-parametrically estimating the jump in the outcome variable between the observations just above and just below the size thresholds for eligibility to the SME scheme[12]. The data is unfortunately very sparse around the threshold[13] to apply smoothing techniques, and the requirement

[12]For a review of these methods, the reader may refer to, among others, Imbens and Wooldridge (2009) and Lee and Lemieux (2010)

[13]Frequencies in relevant employment bins are lower than HMRC disclosure thresholds for us to present evidence for this sparsity.

Figure 8: Median R&D intensity across treatment and control groups



to condition on control variables increases dimensionality. To the parametric model in Equation 1, second, third and fourth order controls for employment, turnover and asset size have been included to experiment with alternative functional forms of the running variables, but these did not alter the results found using the basic specification and hence have not been reported in this paper.

Future work may consider using the difference-in-differences matching approach proposed by Heckman et al. (1998) and discussed in, among others, Smith and Todd (2005), which has the advantage over the parametric diff-in-diff in that it does not rely on the linear functional form assumption.

4.2 Model

We use the following model to identify the causal effect of the 2008 reform on R&D spending:

$$r_{it} = \gamma + \delta_D D_i + \delta_I D_i T_t + \mathbf{x}'_{it}\beta_x + \eta_i + \phi_t + \nu_{it}, \tag{1}$$

where r_{it} is the level of R&D intensity measured by the qualifying R&D spending as a share of total turnover (beginning-of-year) for company i in year t in 2008 prices[14]. D_i is a dummy that takes on a value of 1 for the treated observations and 0 for

[14]In the denominator, the lagged turnover is used as a measure of firm size in an analogous manner to thinking about capital stock in the literature on physical investment.

the control observations. T_t is a dummy that takes on a value of 1 for years 2008 onwards and 0 otherwise. The coefficient δ_I on the interaction term D_iT_t captures the differential change in R&D intensity between pre- and post-2008 periods for the treatment group compared to the control group. The null hypothesis of no impact of the change in the generosity of the tax credit on R&D spending in the treated group relative to that in the control group corresponds to $\delta_I = 0$. Time-invariant unobserved firm heterogeneity in some specifications is captured by inclusion of firm-fixed effects η_i and aggregate macroeconmic shocks that are common to all companies, including the effect of the great recession, are controlled for in all specifications by the set of time fixed effects ϕ_t. Other non-tax determinants of firm-level R&D spending including the firm's growth rate of turnover, age, and profitability (measured as the ratio of lagged trading profits or losses to lagged turnover) are included in the $\mathbf{x}$ vector as additional controls. In alternative specifications without including firm fixed effects, a full set of sector dummies and their interactions with year dummies are also considered as control variables. Two-digit sectors are used based on information provided in FAME.

We estimate alternative specifications based on Equation 1 with three different control samples of Sample Large-750, SME-100 and SME-all, which were explained in Section 3.4. In the main set of results provided in this section, time periods between the announcement of the policy (2006) and its implementation (2008) have been removed and robustness checks with only the period 2008 removed from the samples are provided in the subsequent section.

As suggested in Figure 3, large companies faced a relatively flat tax component of the user cost throughout the 2002-2009 period and in this sense represent a more suitable control group against which we may assess the response of the treatment group to the policy change. Despite the drop in the user cost of capital for SMEs due to the increase in the enhanced deduction rates, this drop is much smaller than that for those companies which switched from large status to being an SME, and the results using the SME control groups are also discussed here. Table 4 presents the regression results based on Sample Large-750 and the model in Equation 1, with a varying set of control variables.

In Table 4 Columns (1)-(4) present pooled OLS results, and Columns (5)-(9) present estimation results with inclusion of firm fixed effects. All specifications include a set of year fixed effects. In all columns, standard errors are clustered at the company level. Column (1) presents the baseline specification with no additional controls. The coefficient 'Treatment' represents the estimate for the δ_D parameter and captures the difference in the average R&D intensity between the treated and control groups in the pre-reform period. This coefficient is insignificantly different from zero in all the specifications, suggesting that, on average, companies in the treated and control groups undertook similar R&D spending relative to their turnover prior to this tax reform. The row labeled 'Diff-in-diff' provides the estimates for the main coefficient of interest which captures the differential effect of the policy reform on R&D spending in the treated group relative to R&D spending in the control group. To assess the robustness of the basic results to industry heterogeneity, column (2) introduces two-digit industry fixed effects and Column (3) adds industry-time fixed effects. The basic finding of a positive and significant policy coefficient remains unchanged. To control for the potential confounding effect of differential firm growth on R&D spending, Column (4) further controls for firm growth rates in real turnover. The basic results remain the same.

Columns (5)-(9) further includes a set of firm-fixed effects to control for potential confounding effects of unobserved firm heterogeneity on R&D investment. Inclusion of firm-fixed effects also controls for potential estimation bias in the parameter of interest due to firm entry and exit, although more than 80 percent of companies are observed in all the years available in the data set. While the diff-in-diff coefficient is positive and significant at the 10 percent significance level in all the columns, inclusion of firm-fixed effects reduces its magnitude from 15 to 12 percentage points. Columns (6) and (7) check the robustness of the baseline result in Column (5) by including a set of two-digit industry fixed effects and industry-year fixed effects, respectively. Column (8) further includes the turnover growth rate, lagged profitability ratio and the age of the company. Finally, Column (9) controls for level differences in R&D investment between profit-making and loss-making companies by including a time-varying 'loss dummy' which takes the value of unity in years where the company reports a trading loss and zero when the company reports a profit[15]. Column (9) summarizes the estimation results using our preferred specification, which includes firm level fixed effects and all the control variables. The estimated effect of the policy is significant at 10 percent level and around 12 percentage points. Considering that in the 2007-08 period, the mean level of R&D intensity for the treated group was 13 percent, an increase of 12 percentage points amounts roughly to a doubling of R&D intensity in the treatment group as a result of the policy reform.

[15]In specifications not presented in this paper, sector-year dummies are also included and their inclusion did not have an effect on the results reported here. OLS results reported in Columns (1)-(4) are robust to the inclusion of the additional control variables firm age, profitability and trading loss dummy.

Table 4: Results with Sample Large-750

	1	2	3	4	5	6	7	8	9
Diff-in-diff	**0.146***	**0.148***	**0.154***	**0.151***	**0.126***	**0.123***	**0.124***	**0.121***	**0.124***
	(0.088)	**(0.087)**	**(0.091)**	**(0.089)**	**(0.070)**	**(0.069)**	**(0.070)**	**(0.069)**	**(0.069)**
Treatment	-0.017	-0.006	-0.009	-0.008					
	(0.022)	(0.024)	(0.025)	(0.024)					
Sales growth				0.088***		0.060***		0.059***	0.059***
				(0.030)		(0.022)		(0.022)	(0.022)
Profitability							0.001	0.001	0.001
							(0.001)	(0.001)	(0.001)
Age							0.006***	0.007***	0.007***
							(0.002)	(0.002)	(0.002)
Loss dum.									0.044***
									(0.013)
Sector FE	No	Yes	Yes	Yes	No	No	No	No	No
Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Sector-Year FE	No	No	Yes	Yes	No	No	No	No	No
Firm FE	No	No	No	No	Yes	Yes	Yes	Yes	Yes
R-sq	0.016	0.071	0.093	0.143	0.018	0.065	0.023	0.067	0.073
No of obs	2628	2628	2628	2621	2628	2621	2601	2595	2595

All standard errors are clustered at the company level.

* stands for significance at 10% level.

** stands for significance at 5% level.

*** stands for significance at 1% level.

Table 5 and Table 6 summarize the estimation results using SMEs as the control group. Specifically, results in Table 5 are based on the Sample SME-100 which includes all the treated observations and the subset of SMEs in the control group with at least 100 employees. Results in Table 6 are based on an alternative control group of SMEs with non-missing employment values. Results in both tables are similar to those obtained using the large control group, with the diff-in-diff coefficient around 12 percentage points and significant at the 10 percent level when firm fixed effects are included. The inclusion of firm fixed effects appear to have a larger effect on the diff-in-diff coefficient when using the SMEs as the control group, suggesting that it is more important to control for the systematic differences in the relation between unobserved firm heterogeneity and R&D intensity between the treated firms and the SME control firms.

As suggested in Column (9) of Table 6, all the control variables including turnover growth rate, profitability ratio, age of the firm and the dummy capturing whether the firm has made a loss in a given period display a positive sign and are significant. Point estimates on these control variables are similar in Table 5, but are estimated with larger variance due to a much smaller sample size around one fifth of all SMEs with non-missing employment values. The main difference between the results reported for Sample SME-100 and the sample of all SME control observations is in Columns (1)-(4) with pooled OLS, where the diff-in-diff point estimates in the latter are very close to those that arise from within groups estimates, whereas the OLS estimates in the SME-100 sample seem to suffer from an upward bias.

Table 5: Results with Sample SME-100

	1	2	3	4	5	6	7	8	9
Diff-in-diff	**0.186****	**0.180****	**0.202****	**0.202****	**0.138****	**0.134***	**0.138***	**0.134***	**0.134***
	(0.088)	**(0.086)**	**(0.097)**	**(0.096)**	**(0.070)**	**(0.069)**	**(0.070)**	**(0.070)**	**(0.070)**
Treatment	0.009	0.011	0.006	0.004					
	(0.023)	(0.028)	(0.031)	(0.028)					
Sales growth				0.081		0.063		0.067	0.067
				(0.052)		(0.041)		(0.043)	(0.043)
Profitability							0.003	0.009	0.009
							(0.018)	(0.025)	(0.025)
Age							0.005***	0.006***	0.006***
							(0.002)	(0.002)	(0.002)
Loss dum.									-0.004
									(0.020)
Sector FE	No	Yes	Yes	Yes	No	No	No	No	No
Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Sector-Year FE	No	No	Yes	Yes	No	No	No	No	No
Firm FE	No	No	No	No	Yes	Yes	Yes	Yes	Yes
R-sq	0.043	0.107	0.182	0.223	0.038	0.073	0.039	0.079	0.079
No of obs	794	794	794	792	794	792	793	791	791

All standard errors are clustered at the company level.
* stands for significance at 10% level.
** stands for significance at 5% level.
*** stands for significance at 1% level.

Table 6: Results with Sample SME All

	1	2	3	4	5	6	7	8	9
Diff-in-diff	**0.119**	**0.129**	**0.119**	**0.121**	**0.131***	**0.125***	**0.128***	**0.123***	**0.125***
	(0.088)	**(0.087)**	**(0.096)**	**(0.094)**	**(0.070)**	**(0.069)**	**(0.070)**	**(0.070)**	**(0.070)**
Treatment	-0.050**	-0.045	-0.043	-0.038					
	(0.022)	(0.029)	(0.026)	(0.026)					
Sales growth				0.100***		0.076***		0.089***	0.090***
				(0.018)		(0.015)		(0.016)	(0.016)
Profitability							0.006	0.009***	0.009***
							(0.004)	(0.004)	(0.004)
Age							0.008***	0.010***	0.010***
							(0.002)	(0.002)	(0.002)
Loss dum.									0.029***
									(0.007)
Sector FE	No	Yes	Yes	Yes	No	No	No	No	No
Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Sector-Year FE	No	No	Yes	Yes	No	No	No	No	No
Firm FE	No	No	No	No	Yes	Yes	Yes	Yes	Yes
R-sq	0.013	0.071	0.092	0.128	0.011	0.05	0.018	0.071	0.073
No of obs	4883	4883	4883	4864	4883	4864	4852	4834	4834

All standard errors are clustered at the company level.
* stands for significance at 10% level.
** stands for significance at 5% level.
*** stands for significance at 1% level.

4.3 Robustness and alternative specifications

We first check the robustness of our findings to alternative cutoff point in employment size in defining the control group. Restricting the large control group to include only the companies that have up to 650 employees, or expanding it to include those companies that have up to 1000 employees produce results that are roughly in line with the findings in the preceding section.

Section 4 imposes the most strict selection of observations to remove any anticipation effect by excluding all the periods that follow the announcement of the policy change and the year of implementation, i.e. between 2006 and 2008. Alternatively, we may remove observations only in 2008 during which the reform took place after the first quarter. Table 7 presents the results from this regression with Sample Large-750, where the point estimates for the diff-in-diff coefficient is 11 percentage points in the preferred specification in Column (8) and is similar to the results in Section 4. However, the diff-in-diff coefficient is estimated with lower precision as suggested by the wider confidence intervals and hence affecting the significance of the results. The pooled OLS point estimates reported in Column (1)-(4) are closer to the estimates which use the within transformation.

The main reason for removing the periods after the announcement and before the implementation of the policy is to overcome the anticipation effects that may be reflected in the results. Firms may react to the announcement of the policy by: (i) postponing their R&D spending to two periods later, when the more generous credits are introduced, (ii) starting to invest early on in preparation for a long term R&D project, (iii) postponing merger and acquisition decisions to until after the policy, or (iv) strategically adjusting the firm size to keep benefiting from the SME scheme both before and after the policy change. Here, (i) and (ii) are countervailing effects, and for each firm the overall strategy may involve one or the other but not both. Removing the years 2006-2008 would address the issues that may arise from back-loading the R&D investment as in (i) above or front-loading the R&D investment as in (ii) above because of the timing of policy announcement. If there is a strategic timing issue of mergers and acquisitions as in (iii) above, then the acquired firm is not captured by either treatment or control groups, since they will fail to satisfy the internal margin condition of having been in the data set and performing R&D both before and after the reform. Finally, the strategic adjustment of firm size to always benefit from the more generous SME scheme is the downsizing effect discussed in Garicano et al. (2013). The predictions in the paper by Garicano et al. (2013) suggest that some less productive firms may 'bulge' just below the threshold for eligibility to the SME scheme, which means that they will initially keep employment below 250 and then expand to a larger size, perhaps not as much as 500 employees but to a larger size than 250. The number of companies that grow just after the announcement or the implementation of the policy is fewer than the disclosure threshold, not allowing us to present an analysis of the behavior of these companies. If these firms are indeed the less productive firms, then the results against the SME control group may have been biased toward our finding an effect of the policy as they would be in the SME control groups because of having consistently been labeled SME. If the productivity differences are roughly stable across time periods, then the firm fixed effects would be sufficient to control for them.

The effect that we find using both the large and the SME control groups is sizeable, and we ran quantile regressions to verify that it is not driven by outliers with very high R&D intensity. The effect of the policy reform is observed to kick in around the 75^{th} percentile of the distribution, and the full effect is realized around the 90^{th} percentile, which means that the largest performers of R&D may be the ones most highly affected by the policy reform. Median regressions do not appear to find an effect of the policy, and future work is intended to focus on such heterogeneities among treated firms.

Table 7: Results with Sample Large-750, including periods 2006 and 2007

	1	2	3	4	5	6	7	8	9
Diff-in-diff	**0.137**	**0.141**	**0.145**	**0.139**	**0.112**	**0.107**	**0.104**	**0.099**	**0.102**
	(0.087)	**(0.087)**	**(0.090)**	**(0.088)**	**(0.082)**	**(0.081)**	**(0.078)**	**(0.076)**	**(0.076)**
Treatment	-0.008	0.002	0.000	0.003					
	(0.021)	(0.023)	(0.023)	(0.022)					
Sales growth				0.082***		0.056***		0.056***	0.056***
				(0.023)		(0.017)		(0.017)	(0.017)
Profitability							0.001	0.001	0.001
							(0.001)	(0.001)	(0.001)
Age							0.006***	0.007***	0.007***
							(0.002)	(0.002)	(0.002)
Loss dum.									0.039***
									(0.011)
Sector FR	No	Yes	Yes	Yes	No	No	No	No	No
Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Sector-Year FE	No	No	Yes	Yes	No	No	No	No	No
Firm FE	No	No	No	No	Yes	Yes	Yes	Yes	Yes
R-squared	0.013	0.079	0.1	0.148	0.015	0.061	0.017	0.061	0.067
No of obs	3720	3720	3720	3710	3720	3710	3676	3667	3667

All standard errors are clustered at the company level.
* stands for significance at 10% level.
** stands for significance at 5% level.
*** stands for significance at 1% level.

Goolsbee (1998) argues that R&D policy is only effective to the extent that there is a large supply of scientists and researchers to increase the R&D stock of companies. Due to the inelastic supply of this high-quality work force, he supports that policies such as the R&D tax credit only work to increase the wages and salaries of R&D employees and do not generate additional real R&D activity. If this observation is correct, then we should observe a positive and significant effect of the reform on the average wages and salaries of treated observations. To test this statement, we estimate the following model:

$$w_{it} = \gamma + \delta_D D_i + \delta_I D_i T_t + x'_{it}\beta_x + \eta_i + \phi_t + \nu_{it}$$

where w_{it} is the total wage and salary relative to the beginning-of-year total sales in company i in year t, and all other variables are as previously defined. Assuming that variation in the total wage bill reflects variation in the wage and salaries of R&D employees, a positive estimate of δ_I would suggest an increase in the R&D-related wage bill due to the policy reform. When including a full set of firm and year fixed effects and additional controls, the point estimate of the diff-in-diff coefficient is negative and statistically insignificant. Assuming that there is no substitution between the R&D labor and non R&D labor input, the result suggests that at least in the short run, the null hypothesis of no effect of the policy on the share of labor costs in output against the alternative of a positive effect cannot be rejected, not providing supportive evidence for the Goolsbee (1998) critique.

5 Discussion

We find that the expansion of the SME tax relief for R&D to companies with between 250-500 employees led to an increase in their R&D intensity by around 12 percentage points, and the effect of the tax incentive is robust to use of different samples as well as alternative specifications. This is a sizable effect, which roughly corresponds to a doubling of the R&D intensity of the treated firms, given that the average pre-reform R&D intensity in the treated group was around 13 percent.

The size of the treatment group is very small, mainly due to the missing SME or large company indicator variable in CT600 despite the report of positive enhanced R&D expenditure. Considering the legislation and administration costs involved in the policy change, it is difficult for us to imagine that the UK Government specifically targeted such a small set of companies that we identify to be primarily affected by the SME definition change. Therefore, more available data in the future from R&D Compliance Units and a possible match with the BERD data set should shed more light on the number of companies that benefited from this reform.

The timing of this policy reform coincides with the beginning of the recession and it is possible that the treatment and control firms may have been impacted differentially by the liquidity constraints that arose around this period, which may be reflected in the diff-in-diff coefficient estimates. In particular, we may expect smaller companies to be hit more severely by a credit crunch relative to larger companies. If this is the case, we would observe a larger tax effect using the SME control groups but not using the large control group. This could potentially explain the slightly larger diff-in-diff point estimates found with the SME-100 control group, but is not consistent with the absence of an upward bias in the coefficient estimate of the tax effect when using SME observations with non-missing employment values.

Wilson (2009) argues that R&D tax credits merely result in a zero sum game where firms shift their R&D activity from higher to lower tax jurisdictions (states) where R&D tax incentives are more generous. The effect found in this paper relies on a quasi-experimental set up and does not make any claims about the route through which we observe higher R&D intensity. There are at least two possible such routes. The first is the cost of capital route, where the reduction in the cost of R&D capital thanks to the more generous tax incentives results in higher R&D investment by the treated firms. Alternatively, the identified tax effect on R&D intensity may be caused by the change in the average tax rate influencing multinationals' location decisions for their R&D activity (Devereux and Griffith (2003)). The methodology used in this paper does not allow us to separately identify such effects. A report by PriceWaterhouseCoopers

(2011) comments, based on a survey, that the R&D tax incentives will have a much larger impact on the companies' 'location decisions' after the implementation of the above-the-line credit, suggesting that the main impact envisaged for the tax incentives comes from a shifting of R&D activity from other countries to the UK.

The current analysis captures the impact of the reform on the intensive margin of R&D investment decision. Using the CT600 data set, the extensive margin effects have also been studied using various cross section and panel binary dependent variable models. Since the companies of interest for the extensive margin are those that did not claim any tax relief for R&D in the pre-reform period, we do not have information on their SME or large status for the purpose of the tax relief. An approximation can be made based on the employment, turnover and asset size of these companies, using the alternative SME definition described in Appendix B. Summarizing our findings on the extensive margin, we do not find that the 2008 SME definition change has a significant effect on firms' decision to invest in R&D. The period of the gravest economic crisis since the Great Depression may not have been an ideal time to start investing in R&D for the medium sized companies that have been studied in this paper and the reduction in tax price may not have been a strong enough incentive to bear the initial fixed costs of starting to engage in R&D. Separately from the timing of this reform and the recession, the extensive margin question in R&D involves a deeper discussion about risk and uncertainty, the discreteness of R&D project opportunities and issues on the financing of R&D projects that diverges from the main focus of interest for this study.

6 Conclusion

The 2006 Budget report of the UK Government emphasizes the importance of medium sized companies in boosting the overall innovation performance of the UK private sector[16]. Guided by this observation, the Government obtained state aid clear-

[16]Government documents refer to a report by Cereda et al. (2005), which presents evidence for the strong performance of medium sized companies in research and development intensity based on data from the Community Innovation Surveys.

ance to expand the more generous R&D tax relief for SMEs to additionally encompass companies that have between 250 and 500 employees, doubling the thresholds required for eligibility to the SME scheme in 2008. This reform reduced the user cost of R&D capital for the relevant medium sized companies by up to 29 percent. The precise magnitude of the reduction in the user cost depended on the tax positions of individual companies and varied amongst the firms that were eligible for the definition change.

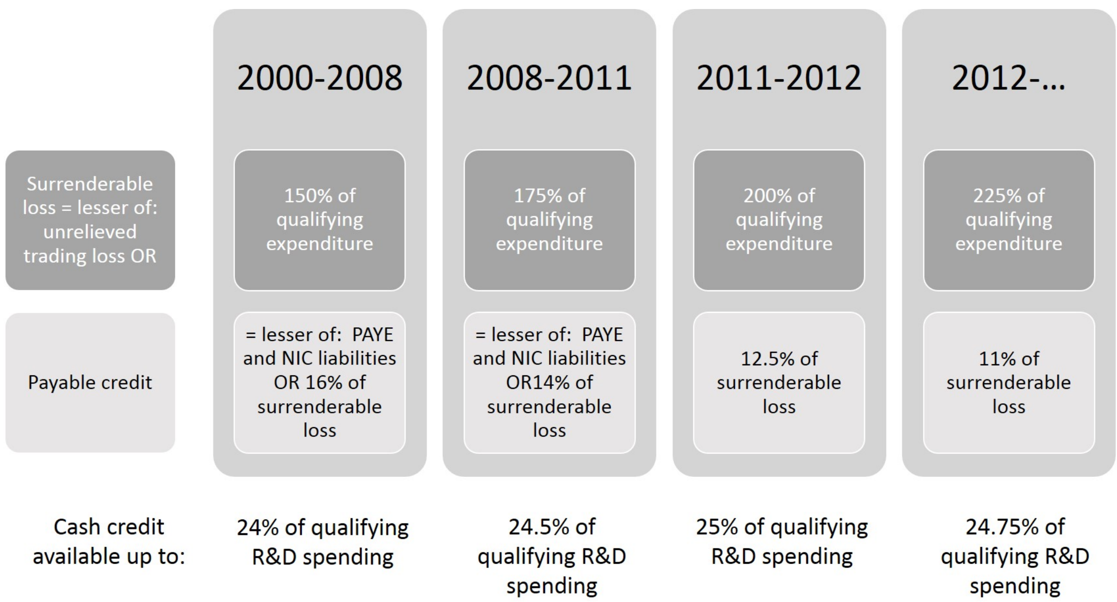
This study used the universe of companies that claimed R&D tax relief in the HMRC Corporation Tax returns panel data set to explore the effects of this policy reform. The use of administrative data has many advantages over survey data for this purpose: first and foremost, we were able to identify the companies that claimed R&D tax relief, and to use the indicator variable to identify which type of relief has been claimed. We were also able to construct a treatment group composed of those companies that have been performing qualifying R&D spending both before and after the policy change. A difference-in-differences set up with company fixed effects has been possible. Having said that, there are two main drawbacks of the data. First, we were unable to observe any R&D that did not qualify for the R&D tax relief and therefore cannot analyze the complementarities between qualifying and non-qualifying R&D. By the same token, we were unable to observe R&D spending by the firms that did not file a claim for their R&D. The second drawback is the missing SME or large company indicators despite the report of positive enhanced R&D deductions.

This study identified the treatment group as those firms which were previously benefiting from the R&D tax relief for large companies and which became eligible for the more generous SME scheme in 2008. Benchmarked against a comparable SME control group which was already eligible for more generous benefits and a large control group whose cost of R&D capital remained roughly stable across time, this study found that the treated firms increased their R&D intensity by about 12 percentage points, corresponding to a doubling of this metric. This result has been found to be robust to the choice of a larger or a smaller set of control observations and the inclusion of control variables such as the growth rate of the firm.

A Cash credits for SMEs

From its inception, the SME scheme has featured a cash component for companies which do not have taxable profits and hence cannot benefit from the enhanced deduction in the year in which the R&D expenditure has been made. HMRC provides a cash refund up to 24 percent of the amount of the total R&D spending of the firm in cash, which is an amount capped by the PAYE or NIC liabilities of the company. If the company is not cash constrained, it has an incentive to carry forward its losses and use the full deduction amount in a future period when it becomes profitable, however, a company with liquidity constraints would choose the cash option which can be claimed immediately. The calculation of the cash amount changed over time, which is depicted in Figure 9, but the total amount of cash available to a company was kept at around 24-25 percent of total R&D spending across periods of different enhanced deduction rates.

Figure 9: Cash Credit Rates for Loss-making R&D Performers



B An alternative indicator to identify SMEs

The R&D tax relief requires that the companies satisfy an employment threshold as the binding constraint and a turnover or an asset threshold as the secondary constraints. In order to be eligible for the SME scheme, the company also has to satisfy the ownership limitations that have been discussed in Chapter 1 of this thesis. In the version of FAME that has been linked to the CT600 data set, ownership information is not available, but the other three criteria have been considered to construct an alternative measure to identify whether the company is an SME or a large company for R&D tax relief purposes. Many observations in FAME have missing values for either the number of employees, asset size, or both. Since the turnover information is sourced by CT600, this variable is non-missing for most of the observations in the merged R&D data set. If number of employees, turnover and asset size are available for an observation, then all three of these have been used in the construction of the alternative SME flag to Box 99. Otherwise, the available information has been used and compared with the appropriate thresholds displayed in Figure 2.

Finally, the criteria for eligibility to the SME scheme is backward-looking, in the sense that a company that qualifies for the SME relief in year t which then exceeds the threshold in year $t + 1$, but goes back to satisfying the SME criteria in year $t + 2$ maintains its SME status in all these three periods. Similarly, if a large company transitions to SME status in one year, but goes back in the following year is not eligible for the SME relief in any of these years. In the alternative SME flag which uses FAME data to label observations that have a positive report of enhanced R&D deduction but missing Box 99 and 100, statutory eligibility criteria and this transition period rule have been used.

Table 8 shows the overlap between the Box 99/100 definition of SMEs that is sourced by the CT600 and the alternative SME flag that is sourced by the FAME accounting data alone.

Out of all the companies that are labeled 'large' in the CT600 form, with a check in Box 100, only 43 percent of them are correctly labeled by the alternative measure

Table 8: Overlap between the CT600 SME indicator and the 'alternative' flag

	CT600	
Alternative	**Box 100=1**	**Box 99=1**
Large	43%	3%
SME	57%	97%
Total	100%	100%

as 'large' and the rest is mistakenly labeled as 'SME'. This may largely be caused by companies that are owned by larger groups and the current version of FAME does not allow for the identification of such companies. Out of the companies that have the SME indicator (Box 99), there is a 97 percent match with the alternative SME flag which is much higher than the success rate in matching the large company flag. Given the information in the current versions of CT600 and FAME, the best that can be done is to first use the alternative flag and then to correct the ones for which either Box 99 or Box 100 information has been provided.

Revising the SME definition as explained in this section increases the number of companies labeled as 'treatment' to more than 130 per year, which is a more realistic estimate of the companies that benefit from the policy change. On the other hand, the companies identified as 'treatment' using this alternative measure are not necessarily also labeled as 'treatment' by the standard measure used in this paper which is only based on the CT600 returns. For example, if a company is identified as large in 2006-07 and SME in 2009-10 by the alternative measure, then it is placed in the alternative treatment group, and if this company is not labeled by the CT600 measure in 2006-07, but labeled as SME in 2005-06 and also as SME in 2009-10, it is placed in the SME control group if the CT600 measure has been used. Only around 20 percent of observations in the alternative treatment group are also placed in the treatment group when the CT600 measure has been used, creating a large discrepancy between the two definitions of treatment given the small sample sizes.

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Chapter 3

R&D, Technology Spillovers and Productivity

Abstract

This paper presents estimates of production functions augmented with the firms' own and external R&D as inputs to the production process. Two main findings emerge: (i) correcting the mismeasurement in labor and materials to account for their R&D components separately improves the own R&D elasticity estimates substantially, (ii) production units of groups with R&D activity benefit from the R&D done elsewhere within the group. The long form responses in the Business Enterprise Research and Development (BERD) Database offer a useful source of detailed information regarding sectors of R&D activity and the components of business R&D expenditure which has so far been underutilized in the literature. I merge this data set with with the Annual Respondents' Database (ARD) of UK manufacturing enterprise groups to estimate production functions. Measures of R&D external to the firm, for which the microfoundations have recently been laid out by Bloom et al. (2013), have been constructed to quantify the productivity effects of external R&D.

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Contents

1 Introduction

R&D spending by private firms can be broadly decomposed into current and capital expenditure, where the current spending on average constitutes around 90 percent of a firm's total R&D (subject to sectoral differences)[1]. In the estimation of a gross output production function with physical capital, labor, materials inputs and knowledge capital constructed from the R&D flow, unless a breakdown of R&D into its labor, capital and materials components is available, the elasticity of output with respect to knowledge capital may be underestimated due to the mismeasurement of other inputs where the cost of R&D labor, R&D materials and R&D capital goods are counted under both the conventional inputs and the amount of R&D (Schankerman (1981))[2].

Within large enterprise groups, production units which themselves do not perform R&D benefit from R&D done elsewhere in the group, but to a lesser extent than the units which perform R&D and have production capability at the same time, which is an effect that is usually overlooked in the literature. Additionally, productivity at the firm level benefits from the firm's own R&D as well as R&D undertaken by others that operate in similar technology fields. Defining 'similar technology fields' is a research question that has been much studied in the spillovers literature, especially since Jaffe (1986), but quantifying knowledge spillovers still poses a challenge for empirical research in this area.

The availability of detailed R&D data enables this paper to address the measurement problems summarized in this section, namely, the double counting of the R&D input, the effect of R&D performed in some part of a large group on its production units which themselves do not perform R&D, and the measurement of R&D external to the firm. This paper uses the UK micro level Business Enterprise Research and Development (BERD) data set collected by the Office for National Statistics (ONS). Differently from many of the studies which use this data set, this paper exploits the detailed information at the product field level for the respondents to the BERD long form questionnaire with the aim of distinguishing: (i) the separate labor (salaries and headcount) and materials components of the R&D input, and (ii) the product field(s) in which the respondents carry out R&D activities and the shares of such activities in total R&D of the respondents. The BERD data set is matched with the Annual Respondents' Database (ARD), which provides information on employment and sector of activity at the plant level, and on capital expenditures, materials, gross output and the total wage bill of respondents at the broader 'reporting unit' level[3].

[1] The reader may refer to aggregate statistics in the OECD Structural Analysis Database for breakdowns at the country and sector level.

[2] In a value added production function, the same problem arises with physical capital and labor inputs.

[3] These ONS surveys provide information at the local unit, reporting unit, enterprise and enterprise group levels which were discussed in detail in Chapter 1 of this thesis and later in Section 4 of this chapter.

The use of detailed information on R&D activity from BERD long form recipients offers a solution to the 'double counting problem' in measuring R&D in productivity studies. This paper estimates that the elasticity of output with respect to a firm's own R&D input is around 2-3 percent and highly significant, while the results from models that do not account for double counting on the same sample find estimates as low as 0.6 percent which are marginally significant at best.

Once the correction for input mismeasurement has been introduced, for units that themselves do not perform R&D, the measure for R&D carried out in the rest of a multi-unit enterprise group is shown to be positive and significant as a factor of production, with a magnitude for the elasticity of output around 0.6-0.7 percent and significant at the 1 percent level.

Bloom, Schankerman and van Reenen (2013) [BSV] emphasize two main channels through which neighboring firms in technology and product market spaces interact with each other and present a model which predicts the implications of R&D spending by these firms. The first prediction relates to the effect of R&D carried out by a neighboring firm in technology space, which is the positive externality arising from the R&D spillover, adding to the knowledge capital of the firm that did not invest in R&D. The second prediction relates to an effect that may be undesirable for the firm that did not invest in R&D, as this effect is caused by R&D carried out by a product market rival, and BSV predicts that such R&D may reduce the market share of neighboring non-R&D firms in product market space. In this paper, I constructed technology spillover measures that align with the recent BSV methodology thanks to the availability of each long form respondent's R&D product field information. In addition, the information on the distribution of production activity to different product fields in ARD local unit data enabled the construction of the BSV proposed measure to capture the effects of product market rivalry[4]. Using these measures, a positive effect of external R&D up to 2 percent has been found, but the effect is not robust to weighting external R&D at the enterprise group level or reporting unit level, or to the inclusion of reporting unit fixed effects. Further research into refining the measures of external R&D by matching with patent data has been suggested for future work.

The remainder of this thesis chapter is structured as follows. The next section presents the theoretical background relevant for productivity estimation and the incorporation of a firm's own and external R&D to such analysis. Section 3 reviews the literature on estimating the productivity of R&D activity, followed by some estimates previously found using UK micro data. Section 4 describes the data sets used in this study and discusses the measures of external R&D. Section 5 presents my estimates of output elasticities before and after including R&D as an input, and then introduces the double counting correction and the measures of external R&D. Section 6 concludes. Appendices are included to expand on the data cleaning procedures and provide the details on the deflators, initial

[4]Differently from BSV, I use the information on different fields in which the firms (enterprise groups) invest in R&D rather than the 'technology classes' in patent data.

value calculations for physical capital stock and sector groupings in the BERD data set.

2 Methodology

2.1 Theoretical framework

The estimation of a gross output production function $Y = F(K, L, M, \epsilon)$ relates the capital, labor and materials inputs to output and with a Cobb-Douglas form, we obtain the following model:

$$Y_{it} = A_t K_{it}^{\beta_k} L_{it}^{\beta_l} M_{it}^{\beta_m} e^{\epsilon_{it}} \tag{1}$$

where Y stands for gross output, K stands for physical capital stock, L is labor input, M is intermediate inputs and A represents the average level of total factor productivity across all firms i and time periods t. ϵ is a firm-and-time-specific shock to productivity, but it also includes all measurement errors and any shocks that are observable to the firm and perhaps unobservable to the researcher. Factor contributions to productivity can be measured by their elasticities, which are captured by the β parameters.

This formulation assumes identical production technology across firms and additive separability of production inputs in their log form. The Cobb-Douglas functional form is convenient for estimation and allows for non-constant returns to scale, but restrictive in the way it allows for substitutability between inputs. More general functional forms, for instance, constant elasticity of substitution (CES) and translog can also be used and the ideas discussed here generalize to these forms. A detailed discussion of the choice of functional forms can be found in Jorgenson (1986).

The seminal work of Griliches (1979) discusses the impossibility of measuring the contribution of 'science' to production, then focuses on the more concrete measure of R&D efforts, demonstrating a channel through which these efforts accumulate to constitute the knowledge base of a firm, an industry or other entity i which has the capability of accumulating such knowledge:

$$\begin{aligned} C_{it} &= c_0 \left[W(B)R_{it}\right]^{\eta} e^{\mu t + \nu_{it}} && (2) \\ W(B)R_{it} &= w_0 R_{it} + w_1 R_{it-1} + w_2 R_{it-2} + \cdots && (3) \end{aligned}$$

where $W(B)$ is a lag polynomial and $W(B)R$ represents the assumed linear structure with which R&D investment R accumulates, μt is the background trend change in knowledge capital over time and ν_{it} is the random error term. Knowledge capital becomes obsolete over time when replaced with new inventions, and the rate at which this occurs is the 'knowledge depreciation rate'. The accumulated knowledge itself cannot be measured, but a portion of it, $G_{it} = W(B)R_{it}$ can be quantified and included in the estimation of a production function.

A key feature of knowledge accumulation that diverges from the accumulation of physical capital is the contribution of R&D efforts that are external, but relevant to the firm due to both 'geographical' and 'technological' proximity (Jaffe (1986)). 'Neighboring firms' in this literature may therefore refer to other R&D performers that are in close geographical proximity or that operate in related industries. The term 'related industry' here is used in a broad sense, as knowledge or productivity in an industry may benefit from inventions in seemingly very different industries. Such closeness will be elaborated on later.

The formulation of Griliches (1979) considers the production function $Y = F(X, C, \epsilon)$ where X represents the inputs other than R&D, and assumes that C is a separable component.

Following this tradition, adding own and external R&D to the model in Equation 1 and expressing in natural logarithms yields (with lower case letters denoting the natural log of the variables) the estimation equation in 4. In this expression, the measurable component of knowledge capital, that is, G_{it} is used. Additionally, this component is modified to incorporate R&D that is external to the firm, but which the firm benefits through spillovers.

$$y_{it} = a_{it} + \beta_k k_{it} + \beta_l l_{it} + \beta_m m_{it} + \beta_o g^o_{it} + \beta_e g^e_{it} + \tau_t \epsilon_{it} \tag{4}$$

where g_{it} is the R&D stock (in log), or knowledge capital of the firm, which has two components: the firm's own R&D stock (g^o_{it}) and the R&D external to the firm (g^e_{it}), which enters the firm's production function through spillovers.

The formulation proposed by Griliches (1979) also embeds quality adjustments to labor, as their omission results in the mismeasurement of the labor input. Specifying $L = QN$ where Q is the quality of labor and N is the headcount measure overcomes this mismeasurement problem in the presence of appropriate quality measures. In this study, I have been able to incorporate such quality adjustments thanks to the availability of both R&D and non-R&D labor cost information, allowing for the construction of relevant average wage variables and their inclusion in the production function alongside headcount employment.

2.2 Quantifying spillover effects

Equation 4 offers a simple representation of the contribution of external R&D stock to firm i's own productivity. Several channels have been examined in the literature to explain such contribution, with the main ones being technological and geographic proximity of firm i to innovative firms. Jaffe (1986) and Bloom et al. (2013) [BSV], among others, have discussed both the positive and the negative effects of proximity in R&D intensive industries, where the positive technological spillovers are challenged by countervailing competition effects. A firm benefits from the research activities of neighboring firms in technology space, but there is also the risk that neighboring firms in product space may 'steal' each others' customers through product and process innovations, leaving the net effect of proximity to depend on the nature of competition within industries.

One way of defining the total spillover pool of a firm is to consider a weighted sum of all R&D external to the firm. The weights can be determined in the traditional way[5], using the distribution of R&D activity across different technology classes within a firm. A more elaborate weighting of a firm's external R&D could use the firm's closeness in technology space to each of the other firms. In Jaffe (1986), each firm is assumed to carry out research activities in a number of fields. Using technology classes of each firm's patents as a proxy to identify their 'location' in technology space, the knowledge production process can be formalized as a function of current R&D spending, the spillover variable, its interaction with R&D spending and technology shocks specific to each 'technology cluster'. Microfoundations of the Jaffe (1986) measure are provided in BSV, which attributes the weights of neighboring firms' R&D to a 'probability of encounter' between the scientists of pairs of firms and calls this weighted spillover measure the 'exposure measure of proximity'. In the empirical application of BSV, the stock of scientists is replaced by the R&D stock measure. BSV also introduces a Mahalanobis extension to the Jaffe (1986) measure which takes into account the distance of technology fields from each other and allows spillovers to occur across fields that are close each other. This measure assigns probabilities for knowledge spillovers among field pairs.

The theoretical model of spillover effects presented in BSV is based on a two stage game where firms first interact in technology space and then in product space. In the first stage, firms decide on their level of R&D, and R&D by neighboring firms in technology space is beneficial for the knowledge base of each other. In the second stage, innovations may have a direct effect on profits or an indirect effect working through prices (or quantities if the firms compete in quantities). BSV estimates four equations in line with this set up, where these interactions determine: (i) market value, (ii) patents, (iii) productivity, and (iv) R&D intensity. For the purpose of this paper, the relevant predictions relate to the productivity equation in BSV. BSV quantifies the interactions in technology and product space using the Jaffe (1986) measure and their Mahalanobis extension.

The Jaffe (1986) technological distance measure considers the 'technology profile' of each firm that is constructed using a vector which has as its elements the shares of the firm's patents in technology classes. If patent information is not available, the same idea can be applied to the shares of R&D spending in different product fields, technology classes or the relevant sector classification that is available in the data. In this study, the data allows for the location vectors to be defined in terms of the shares of R&D spending in different product fields. The location vector for each firm can then

[5] Use of industry totals to measure intra-industry spillovers can be found in, among others, Bernstein and Nadiri (1989).

be defined as $X_i = (X_{1i}, X_{2i}, ..., X_{pi}, ..., X_{Pi})$, with X_{pi} denoting the share of firm i's total R&D undertaken in product field p in an economy which features a total of P product fields[6]. Weights can be constructed using the uncentered correlation between the locations of pairs of firms ij:

$$W_{ij} = \frac{X_i X_j'}{(X_i X_i')^{1/2}(X_j X_j')^{1/2}} \tag{5}$$

which is a scalar. Then the level of R&D external to the firm can be calculated as: $G^e = \sum_{i \neq j} W_{ij} G_j^o$.

BSV develops the Jaffe (1986) measure to allow for closeness between product fields or technology classes to also generate spillover effects. Such proximity is identified using the R&D profiles of the firms themselves; if the R&D profiles of multiple firms feature similar sets of product fields or technology classes, the Mahalanobis distance metric treats these categories as 'close'. In this paper, I focus on the Jaffe (1986) measure of closeness in the empirical section, along with broader sector aggregates. In preliminary investigations with the data not presented in this paper, I explored alternative measures including the Mahalanobis extension of BSV, which did not produce very different results than those using the Jaffe (1986) measure.

BSV lists a set of desirable properties for spillover measures which can be summarized as: (i) being microfounded, (ii) being scale invariant, (iii) accounting for overlaps within technology classes or product fields, (iv) accounting for closeness of technology classes or product fields to each other, (v) firm i's external R&D being invariant to the changes in other firms' R&D profiles if they do not have any technology class or product field overlap, (vi) being robust to aggregation of technology classes or product fields. BSV offers some economic microfoundation for the Jaffe (1986) and BSV Mahalanobis measures, however, the Jaffe (1986) measure fails to satisfy (iv) and (v) above, whereas the BSV Mahalanobis extension to this measure does satisfy (iv), despite failing on (v), and both these measures are superior to crude sector totals of R&D, which, as a spillover measure fails all of the properties listed above.

This paper focuses on Equations 1 and 4, which have become standard ways of representing the production technology for estimation in this literature. These benchmark equations will first consider the effect of own R&D on firm-level productivity, then move on to discuss the effects of total R&D performed by the private sector in a product field, and then external R&D performed by firms with similar technological profiles using the Jaffe (1986) and the BSV methodologies.

An earlier study by Adams and Jaffe (1996) calculates TFP using the index number approach, by substituting the shares of input costs in total output for the firm-specific output elasticities β_{ki}, β_{li}

[6] The BERD questionnaire distinguishes between 33 broad product fields (listed in Appendix B), which are close to two-digit SIC sectors. Among the 33 product fields, some high tech sectors are represented at the three digit detail (for example, Pharmaceuticals), in which case the two-digit sector excludes the particular three digit sector which has a separate product field (for example, Chemicals excludes Pharmaceuticals). Some lower tech sectors such as Agriculture, Hunting, Forestry and Fishing are bundled together.

and β_{mi}:

$$tfp_{it} = y_{it} - (\beta_{ki}k_{it} + \beta_{li}l_{it} + \beta_{mi}m_{it}) \quad (6)$$

The calculated TFP measure is then used to estimate the effect of the firm's knowledge on productivity, where the knowledge measure has the following form:

$$G_{it} = \left[\frac{(R^c_{it} + \delta R^d_{it})^{\beta_f}}{(n^c_{it})^{\gamma_c}(n^d_{it})^{\gamma_d}}\right]\left[\frac{S^{\beta_s}_{it}}{N^{\gamma_s}_{it}}\right] \quad (7)$$

where distance is considered as a binary variable differentiating between 'close' and 'distant' R&D locations in technology and geographic space separately[7]. Intuitively, the sub-/super-scripts c and d denote 'close' and 'distant'. For instance, R^c_{it} denotes R&D undertaken by the parent firm of plant i in a location that is close to the production facility. Here, a steady state assumption allows for the proportionality between knowledge stocks and knowledge flows, therefore the terms R are flow variables[8]. n captures the number of plants belonging to the same enterprise group, whereas S denotes R&D (flow) carried out in labs that are not owned by i's parent firm (weighted using the Jaffe (1986) methodology), and N denotes the total number of plants in the sector to which firm i belongs. The 'number of plants' adjustment brought about by the inclusion of the n variables aims to reflect the possibility that costs of knowledge transfer may increase with a larger number of separate locations for a given firm. TFP is regressed on the natural logs of the components of this knowledge measure and some other control variables to estimate the effects on productivity. I have explored specifications in line with the ideas presented in Adams and Jaffe (1996), but the number of plants in close and distant locations did not appear to make a difference regarding the elasticity of output with respect to own or external R&D. These results are not included in this thesis.

2.3 Estimation of production functions with R&D as an input

Griliches (1979) discusses the estimation of an R&D-augmented production function assuming a Cobb-Douglas form as in Equation 4, with the inclusion of a knowledge capital term $G^{\beta_o}_{it}$. In addition to the well-known simultaneity (Marschak and Andrews (1944)) and selection problems that concern the estimation of production functions at large, there are some additional measurement and estimation issues that arise in the R&D context. Hall et al. (2009) group these challenges into three categories: (i) measurement of productivity, (ii) measurement of knowledge capital, and (iii) econometric issues. This section considers each of these in turn, followed by a discussion of some estimates found in the

[7]The Jaffe (1986) and BSV distance metrics can be adapted to the geographic context to measure geographic spillovers.

[8]This steady state assumption is discussed in Section 4 below.

existing literature in Section 3.

The use of deflators in the measurement of inputs and outputs should ideally take into account the quality upgrades that come along with product and process innovations. Because it takes time for price indices to incorporate a new invention in the basket, generally the indices do not fully reflect the necessary quality adjustment especially required in R&D-intensive products. This issue has been pointed out in the earlier work by Griliches (1979), and with panel data, a proposed practical solution is to include a set of time dummies for each sector to capture such quality trends, which resolves the issue unless there are high intra-industry quality changes (Hall et al. (2009)).

The measurement of output presents a challenge which is difficult to address in the absence of firm-specific prices, although the availability of industry-specific price information offers a partial remedy, to the extent that price differentials are not dramatic within industries (or time-invariant if the panel dimension is used). The difficulty may arise from the lack of knowledge on firm-specific prices and/or output mix. Klette and Griliches (1996) show, in a panel setting using the Cobb-Douglas production function, that the use of a sales measure deflated using a common price index for all the firms and industries instead of a real output measure as the dependent variable can cause a downward bias (and inconsistency) in the estimates for input elasticities. They quantify the size of this bias and show that the magnitude of the bias depends on the partial correlations between the inputs and the common price index used to deflate sales. Two channels are suggested to be responsible for the downward bias: first, higher costs due to quality adjustments in inputs lead to higher prices and lower market shares. Second, firm-specific positive productivity shocks cause more productive firms to lower prices and gain market share, employing a larger quantity of inputs (where demand is elastic). In this study, I use the narrowest possible industry classification for price deflators that can be obtained from the Producer Price Series from the Office for National Statistics, include time dummies and experiment with including controls for the growth in industry output, but as mentioned, these only offer partial remedies to the problem.

Knowledge capital is a notional stock measure of the research base of a firm (Griliches (1979)). According to the perpetual inventory method, the law of motion for knowledge capital follows a special case of Equation 2:

$$G_t = R_{t-1} + (1-\delta)G_{t-1} \tag{8}$$

where R&D flow R_{t-1} contributes to the stock of knowledge capital in the following period t, which depreciates at the constant geometric rate δ. Given this timing assumption, the stock of knowledge capital is the sum of previous period stock (net of depreciation) and the R&D investment carried out in the previous period. Alternatively, it may be assumed that the R&D investment in period t contributes to the knowledge capital stock in period t, analogously to the accumulation of physical capital. Some alternative specifications for the evolution of the knowledge stock have been introduced by, among others, Doraszelski and Jaumandreu (2013) and Klette (1996).

Using a steady state assumption for the pre-sample period with a constant R&D growth rate of g and depreciation rate δ, it can be assumed that R&D capital accumulates prior to the sample period according to the following rule (Hall and Mairesse (1995)):

$$G_1 = R_0 + (1-\delta)R_{-1} + (1-\delta)^2 R_{-2} + ... \tag{9}$$

$$= \sum_{s=0}^{\infty} R_{-s+1}(1-\delta)^s \tag{10}$$

$$= R_0 \sum_{s=0}^{\infty} \left[\frac{1-\delta}{1+g}\right]^s \tag{11}$$

$$= \frac{R_1}{g+\delta} \tag{12}$$

Determining the rate of depreciation for knowledge capital and calculating the initial knowledge stocks present separate measurement challenges. Depreciation in the R&D context can be thought of as obsolescence, which is then dependent on the behavior of the firm's competitors and also the R&D efforts of the public sector. There are some studies which focused on the estimation of depreciation rates for R&D, where estimated rates hover between 15-30 percent (See, for example, Bernstein and Mamuneas (2006), Pakes and Schankerman (1984), Hall (2010)). Hall et al. (2009) report that the studies which experiment with different depreciation rates usually use 15 percent and do not find significant differences across elasticity estimates when different depreciation rates are assumed.

Among the components of knowledge stock, the only observed quantity usually is the expenditure on R&D, possibly with a breakdown into subcomponents such as human resources, materials and capital equipment. The accumulation of knowledge capital is therefore assumed to be based on all the past research flows. Given that the main components of R&D spending are on labor, capital and materials; the usual measures for these inputs that do not distinguish between their R&D and production components mismeasure the inputs that are used directly in the production process[9]. Schankerman (1981) shows that unless corrected for, such mismeasurement results in downward biased TFP estimates if the 'growth accounting' approach is used and also downward biased elasticity estimates of output with respect to R&D[10]. Using lagged values for the R&D or knowledge capital inputs do not resolve the problem. Correcting for double counting in the R&D input requires detailed data on the

[9] Such mismeasurement is not limited to the R&D components of the inputs. For example, personnel eemployed in the marketing (or other non-production) division of the firm is also not part of the input into the production process.

[10] Schankerman (1981)'s derivation treats the portions of inputs that are knowledge-related and should be subtracted from traditional inputs as omitted variables. Therefore, assumptions about the timing of the R&D or knowledge input does not affect the overall conclusion drawn from his analysis as long as these knowledge-related portions are correlated with the components of the R&D or knowledge capital measure that is included in the regression and the output measure used.

cost breakdown of R&D into labor, capital and materials components, which can then be subtracted from the appropriately timed measures of total labor, capital and materials included in the production function. Unfortunately, R&D data at the firm level on many occasions do not contain such detailed information. Hall et al. (2009) review some empirical papers that provide evidence for the downward bias due to double counting, including Hall and Mairesse (1995).

Finally, the firm-level R&D series are usually very persistent, causing most of the variation in panel data to arise from between cross-section observations rather than from time variation within firms. Part of the persistence may be caused by the nature of investment opportunities, where a firm takes on an R&D project to which it commits with a certain share of resources devoted to this activity for lengthy periods of time. Regarding the nature of research-related costs, considering that about half of R&D spending is on skilled labor, it is also plausible that a firm cannot easily hire or fire researchers without the emergence of a new investment opportunity. The dominance of between-groups over within-groups variation has been observed frequently in the literature. Studies often find positive and significant OLS estimates of R&D elasticity while the significance perishes and the point estimates collapse to zero when a panel transformation such as within groups or first differencing is used to remove time-invariant component of the error terms (See, for instance, Hall and Mairesse (1995)).

The extent to which the measurement issues can be addressed in production function or TFP estimates depends on the availability of rich data on the various components of R&D. Some examples of the estimates for the productivity of R&D in the international literature are outlined in Section 3.1, with a summary of how they address the measurement issues and econometric challenges. Estimates reported in studies which use UK data are discussed in Section 3.2.

3 Review of previous empirical work

There is a vast number of studies which estimate R&D elasticities of output or private returns to R&D, conducted using micro data internationally. Two major types of data sources are used: (i) consolidated or unconsolidated company accounts, and (ii) official statistical agency surveys, where the unit of observation may be more disaggregated. Company accounts data are primarily collected to report financial information about firms, whereas survey or census data from official government sources has the advantage of focusing on production inputs and outputs, which is what the researchers in this field try to measure. Official statistics also usually have wider coverage of smaller firms.

The literature has long searched for appropriate measures to quantify knowledge flows between firms (as well as other creators and users of knowledge such as public and private research institutions). R&D surveys similar to the UK BERD, data on patents and patent citations, and innovation surveys such as the Community Innovation Surveys (CIS) have provided researchers with information that can be used to proxy the interactions between innovative firms. Knowledge spillovers may take place between different actors involved in the regional innovation systems, such as universities, research and development institutes, and users of innovation in addition to private sector firms. The discussion in this paper is largely limited to the interactions between businesses, but a few papers which explore other connections are also mentioned where relevant.

Perhaps the most commonly used measure of technological proximity has been patent citations and references to the cited innovator's sector and geographic information (Crespi et al. (2008)), with the caveat being that a lot of knowledge derived from innovative activity which is transmitted across firms is not based on patentable inventions. For this reason, measures based on R&D inputs or measures of innovative outputs have also been used to trace spillover effects across firms.

In the remainder of this section, first, I briefly provide examples of international studies, with the aim of highlighting the different data sources used and the elasticity estimates found in the literature. A comprehensive review of this literature can be found in Hall et al. (2009)[11]. I first outline examples of studies which use data from outside the UK and estimate elasticities of output with respect to the firms' own R&D, before presenting a few studies which incorporate spillover effects. I then move on to discuss examples from the studies that use UK data, including the BERD and ARD databases used in this study.

3.1 Studies on R&D and productivity outside the UK

In the US, the main official micro data set which is made available by the US Census Bureau and frequently used in the literature is the Longitudinal Research Database (LRD), which links real economy variables from the Economic Census or the Annual Survey of Manufacturers (ASM) with the National Science Foundation (NSF) R&D data[12]. The unit of observation in this data set is the company, and the micro data is aggregated to produce the national R&D statistics which are published annually. Official survey or census data have several advantages over the company accounts data sets, which are usually available only for large companies and published for other purposes than providing information on R&D. A publicly available accounting database on consolidated global accounts of US companies is Compustat, which is provided by Standard and Poor's. In Continental Europe, as in the UK, equivalent data sets to the UK's BERD or the US's LRD are collected by the national statistics offices for use in generating aggregate statistics on R&D. Production surveys or censuses similar to ARD and ASM are also available. There are several sources of company accounts data, including

[11] With regard to the production function estimation literature more generally, an in-depth review of the methodologies would require a discussion on the transmission bias and selection issues and the techniques developed to address these problems (such as Blundell and Bond (1998), Ackerberg et al. (2006)).

[12] Until 2007, the Industrial Research and Development Information System and from 2008 onwards, Business Research and Development and Innovation Survey.

Bureau van Dijk - provider of the Amadeus Dataset on European firms and the Financial Analysis Made Easy (FAME) Dataset on UK firms, which have been heavily used in the literature.

A study which uses Computstat data for the US is by Griliches and Mairesse (1984), who examine a balanced panel of 133 large companies over the period 1966-1977 using pooled OLS and within groups (WG) estimators. With deflated sales as their dependent variable, OLS results indicate that the elasticity of output with respect to knowledge capital is about 6 percent. A sharp decline in this elasticity estimate is observed when WG results are taken into consideration; the point estimate of the elasticity becomes insignificant at conventional levels of significance. The authors attribute this decline to the reduction in variation as the between-group variation is removed from the data. They also discuss the possibility of collinearity between R&D capital and physical capital when the firm-specific effects are eliminated.

In their study of 197 French manufacturing firms, Hall and Mairesse (1995) estimate, by OLS, WG, first difference transformation (FD) and long-differencing[13] (LD), a similar form of R&D-augmented production function. Deflated value added is used as the measure of output and estimates for the elasticity of output with respect to R&D are found to vary between 5 and 25 percent. They use book value proxies to measure the physical capital input. For the knowledge capital, they employ a perpetual inventory method, assuming a depreciation rate of 15 percent, and pre-sample real R&D growth rate of 5 percent.

Jaumandreu and Mairesse (2010) simultaneously estimate the production function alongside the demand equation for the firm's output. Estimation of their model requires firm-level data on input and output prices and the nature and timing of innovations, which is more detailed than can usually be accessed, and much more detailed than the data set that is used in this project. The ideas in Jaumandreu and Mairesse (2010) originate from Griliches (1979) and Griliches and Mairesse (1984), who argued that the production function estimation is never complete without a system of equations determining both the demand and the supply sides. Key in this framework is to find an adequate number of exogenous variables as determinants of the endogenous variables. As discussed earlier in this section, inputs to production can be endogenously determined. Under imperfect competition in output markets, output price will also be endogenous. Exploiting duality theory, Jaumandreu and Mairesse form a system of equations using: (i) cost function, (ii) input demand functions, (iii) output demand, and (iv) pricing rule. They empirically test this model using an unbalanced panel of about 1,000 Spanish manufacturing companies over 10 years. Findings on the effect of innovation in the process indicate that product innovations boost output demand and process innovations reduce marginal costs. This model also has the advantage that it is able to yield welfare implications; the authors report gains in welfare of up to 4 percentage points in the sum of consumer surplus and profits as a result of product innovations (See also the seminal papers by Doraszelski and Jaumandreu (2013)

[13]The difference between the last and the first observations.

and Crepon et al. (1998) for other commonly used estimation methods).

Theoretical insights from Adams and Jaffe (1996) and Bloom et al. (2013) were introduced in Section 2. Here, the empirical findings in these papers are presented briefly as examples for the types of spillovers considered in the literature. Both studies use firm-level panel data from the US.

Adams and Jaffe (1996) focus on the chemicals sector in the Longitudinal Research Data (LRD), where the unit of observation is closer to the 'reporting unit' level that is the basis of ARD and BERD surveys in the UK, but it may cover a larger unit than the reporting unit in the case of groups of firms. Using the Annual Survey of Manufacturers, Adams and Jaffe (1996) are able to observe plant level information on production-related variables, but not on R&D. They present both plant-level and firm-level results, where plant-level regressions use total R&D at the company level. Adams and Jaffe (1996) consider both stock and flow measures of R&D and for external R&D, and use the weighted R&D of neighboring firms in: (i) technology space with the distance weights obtained from the distribution of the firms' R&D spending across the three digit product fields within chemicals and (ii) geographical proximity, which is captured by a binary dummy variable that takes a value of unity if the R&D lab is not further away than 100 miles from the production plant. Their first important finding is that the coefficient on the firm's own R&D is insignificant unless the number of plants attached to the firm is controlled for. As number of plants attached to the firm increases, the productivity of the firm's R&D, aggregated across all observed plants in the US, is reduced. The authors do not discuss whether these are firms with only domestic operations, as potentially the estimates may overlook the production activity that takes place in foreign subsidiaries, which may also be benefiting from the R&D done in the US. Second, after controlling for the number of plants, they estimate that the elasticity of output with respect to the firm's own R&D is about 5 percent, and to external R&D is about 7 percent. The productivity of own R&D is found to be 'diluted' as the plants are located further away from the R&D lab. The results hold in the cross-section dimension, but not when the data are transformed to eliminate firm-specific fixed effects.

There is stronger evidence for spillovers in technology space rather than geographic space in the literature. BSV proposes a way to disentangle the product market competition effects from positive technological spillovers (as outlined in Section 2), which may be argued to help in separately identifying these two countervailing forces. BSV uses Compustat and US Patent and Trademark Office data sets, and estimate the R&D, productivity and market value equations using within groups estimation. Thanks to the long time series dimension of their data, within groups proves to be a viable estimator, nevertheless, they have a valid and informative instrument available which is used in robustness checks. The use of instrumental variables estimation (changes in the Federal and State Tax Incentives for R&D to instrument for R&D spillovers) produces point estimates that are larger in magnitude when estimating the effect of technology spillovers on all their outcome measures, namely, R&D intensity, productivity, patenting and market value. Product market rivals' R&D has an insignificant effect on productivity, R&D and patenting, but a negative effect on market value.

3.2 Studies on R&D and productivity that use UK data

In this section, I refer to studies which estimate the R&D elasticity or the rate of return to private R&D using micro level data on UK firms. To my knowledge, none of the studies on the UK have so far used input measures that are corrected for double counting, which is only possible using the information from long form recipients in the BERD data set. I first provide examples which focus only on the elasticity of output with respect to the firm's own R&D, and then discuss a paper which considers spillover effects (Sena and Higon (2012)).

Rogers (2010) emphasizes the scarcity of firm-level productivity studies on UK firms, especially in comparison to those undertaken for the US. Recently, a larger number of researchers have been able to access the Office for National Statistics micro level data, which resulted in an increase in the number of studies on R&D and productivity in the UK. I review some of these, after discussing some papers which use other data sources.

As an example of a study that uses company accounts data[14], Rogers (2010) estimates returns to R&D in the UK over the period 1989-2000. The estimation equation is derived from a Cobb-Douglas production function with capital, headcount labor and R&D flow as inputs. All variables are measured in their period t values. As common in the literature, the paper uses a rearrangement of terms in the production function to then estimate returns to R&D, with the equation in first differences of the output measure and all other inputs than R&D, except the R&D intensity (R&D as a share of output), which enters the equation in levels. The estimation methods are OLS and 2SLS (lagged levels as instruments) in the cross-section and first differencing transformation in the panel dimension. Using a measure of value added as the dependent variable, the paper finds elasticities of output with respect to R&D in the range of 12-16 percent for the manufacturing sector.

In a comparative study of manufacturing firms in the UK and Germany, Bond et al. (2003) use system GMM to estimate a dynamic model of R&D-augmented production functions for both countries. They use nominal sales (measured in year t) as the output measure and R&D expenditures (also measured in year t) as the R&D input. In the dynamic specification, a lagged dependent variable and first lags of all inputs are included as explanatory variables. The data used in this study for the UK are from Datastream International, covering worldwide consolidated accounts of listed companies on the London Stock Exchange for the period 1987-1996. For the British companies, they find statistically significant elasticity estimates with respect to R&D input of about 6.5 percent.

For the R&D input, Bond et al. (2003) consider both the flow of R&D expenditures and the

[14]'Company Analysis' data provides balance sheet and income statement information sourced by Thomson PLC and Extel Financial. R&D is available for the largest firms only, which are required to report R&D spending in their financial statements.

knowledge stock. They calculate the stock variable by applying a perpetual inventory method with a depreciation rate of 15 percent. The construction of initial values for this variable assumes that the R&D stock in steady state is proportional to the flow of R&D (Griliches (1979)). The construction of physical capital involves the application of the perpetual inventory method on the investment flow using a depreciation rate of 8 percent, with initial values based on historical cost accounting measures. Regarding the assumed depreciation rate for R&D capital, Hall and Mairesse (1995) demonstrate that the assumption over this value does not affect the elasticity estimates considerably.

An early example of the studies that use ONS micro data sets in the R&D and productivity context is by Rogers (2006), who estimates elasticities of output with respect to R&D for both manufacturing and non-manufacturing firms for the period 1996-2003. At this point, it is informative to introduce the unit of observation in the ONS micro level data sets. Both BERD and ARD data sets are collected at the 'reporting unit' level, which may cover more than a single 'local unit', which is a plant. Plant level data from ONS and administrative sources is available through the Inter-Departmental Business Register (IDBR) and can be matched with the ARD. IDBR provides basic enterprise level information on plant location at the post code detail, sector of activity, number of employees, legal status and ownership linkages. Further information on these data sets is provided in Section 4.

Rogers (2006) combines information from the BERD data set with the Annual Respondents Database (ARD) matched on reporting unit references, and restricts attention to those reporting units with some positive R&D at the reporting unit level. Based on a static specification and using OLS and first difference transformation with the unit of observation as reporting units with positive R&D, Rogers (2006) finds elasticities of output with respect to R&D in the range of 9-12 percent for manufacturing firms and 6-11 percent for firms in other sectors. The study does not consider measures of R&D external to the reporting unit and emphasizes that issues about simultaneity and the lag structure of the R&D variable have not been addressed.

There have been attempts to produce plant level estimates of productivity using the ARD data, by apportioning reporting unit-level input and output data to individual plants using the employment shares. An example of the available plant level studies is by Harris and Moffat (2011), where the authors estimate production functions using System-GMM (Blundell and Bond (1998)) and interpret the effects of R&D, presence of multiple plants per firm, foreign ownership and agglomeration forces (closeness to other plants) on TFP. They show that performers of R&D have higher TFP than non-performers, except in low and medium low technology manufacturing sectors. Harris and Moffat (2011) uses a stock measure of R&D apportioned to the plants using their employment shares in each reporting unit.

Outside the context of the productivity of R&D, there is a large number of studies that consider the effects of foreign ownership, entry and exit, FDI flows, university-industry linkages technology adoption and related factors on productivity and which use the ARD firm level data. For some examples, the reader is referred to Griffith (1999), Disney et al. (2003), Abramovsky and Simpson (2011), Harris and Trainor (2005), Harris and Robinson (2003), Criscuolo and Martin (2009), Harris and Li (2009).

A recent paper on the UK by Sena and Higon (2012) uses ARD data for the period 1997-2002 matched with BERD and the Labour Force Survey data to analyze the relationship between a plant's 'absorptive capacity' of R&D spillovers and the relative 'educational attainment' of the workforce in the region and the industry in which the plant is located. The plant-level information in this context is equivalent to that at the reporting unit-level, as the data set used in the study only considers those reporting units which comprise a single plant in the ARD. The BERD component of the data includes both imputed and non-imputed values. In order to address their research question, the authors specify a production function with capital, labor, materials and R&D stock as the independent variables and gross output as the dependent variable, using year t values of all variables. This specification involves a total factor productivity (TFP) term, which captures inter-industry R&D spillovers and the relative educational attainment of the region and sector in which the plant is located. They include plant fixed effects and an AR(1) error component. The TFP term is then specified as a function of a spillover measure, the distance from the educational attainment frontier (the 'gap variable'), an interaction term between the spillover and the gap variables, all measured in year $t-1$, a set of control variables and error terms. The specification is estimated using System GMM.

Spillovers are calculated using the total R&D in a region or a two-digit industry, with output weights from input-output data (in the spirit of Terleckyj (1980)). This spillover measure relies on inter-industry relationships considering the input supply relationships between industries, using the Leontieff inverses as weights. The idea of using industry weighted sums of R&D spending aligns with one of the sector level spillover measures that I construct in this study and present in Section 4, but the Terleckyj (1980) weights assume that the R&D spillovers occur through input supply relationships between firms, and it becomes difficult to distinguish input supply relationships from spillover effects. Based on the set up described here, Sena and Higon (2012) find that R&D spillovers result in higher productivity for plants that are located in regions where the educational attainment gap (to the frontier region with the highest measure of educational attainment) is the smallest in the plant's main sector of activity, demonstrated by a negative and significant coefficient on the interaction term between the spillover and the gap variables.

4 Data

4.1 ONS data sets

4.1.1 Annual Respondents' Database (ARD)

ARD is a panel data set of reporting units representing both manufacturing and services sectors of the UK economy. The underlying data sources are the Annual Census of Production (ACOP, 1970-1997), Annual Census of Construction (ACOC, 1992-1997), Annual Business Inquiry (ABI, 1998-2008) and the Annual Business Surveys (ABS, 2009-current). The version of ARD used in this paper covers the manufacturing sectors' information over the period 1998-2008, which is an internally consistent portion of ARD in terms of sampling, variables and questionnaires used in collecting the data set. For this version, the sampling fractions which are based on reporting unit level employment groups are as presented in Table 1.

The main statistical unit in the ARD is the reporting unit, which may represent more than one plant, so it is a higher level than a 'local unit'. One level above the reporting unit is the 'enterprise', which is the smallest autonomous decision-making unit, which in turn may be part of a larger 'enterprise group'. If an enterprise has plants in multiple locations, these may be represented by a single reporting unit or multiple reporting units. Multiple enterprises under common ownership are labeled as an 'enterprise group', and the data set comprises both single enterprise and multi-enterprise groups. Enterprise groups are characterized by some sort of common ownership ties, and I therefore use 'firm' interchangeably with 'enterprise group' for the remainder of this paper. In the whole manufacturing ARD, reporting units typically have a single local unit (95 percent of observations) and the remaining 5 percent have multiple local units. The estimation samples focus on active and continuously sampled reporting units, shifting the focus to larger reporting units, which are part of multi-enterprise groups (around two-thirds of the groups in the samples have multiple reporting units).

Table 1: Annual Business Inquiry Sampling Fractions

Size	ABI fraction
<10 employees	0.25
10-99 employees	0.5
100-249 employees	0.5
250+ employees	All, long form

The sampling frames for ARD and many other ONS data sets are based on the Inter-Departmental Business Register (IDBR), which gathers basic enterprise level information from administrative sources HMRC (VAT traders and PAYE employers) and Companies House on employment, firm age, location and sector information, and ownership linkages from Dunn and Bradstreet. Employment, five-digit sector and location information is available also at the local unit (plant) level.

The ABI form asks that the returns correspond to the period ending 31 December of the given year (year t). In case the respondent reports data for a business year, then the ABI form instructs that a period which ends between April 6 of year t and April 5 of year $t+1$ is covered. The data in the ARD for the flow variables gross output, value added, intermediate inputs and total employment costs refer to the same period. A discussion on the timing of capital, R&D and employment headcount is presented later in this section.

ABI now encompasses, in addition to manufacturing, a large number of service sector enterprises, including the 'business services' field, which includes many R&D labs. The estimation samples for the production functions used in this study restricts attention to reporting units in the ARD's 'manufacturing' data set, that are observed at least for two consecutive periods over the period of interest with positive values for employment and intermediate inputs. Information from BERD which is used to calculate enterprise group level R&D and the measures of R&D external to the firm are not restricted to come from these reporting units. The capital stock values are calculated using a perpetual inventory method. Therefore, non-missing investment information in at least two consecutive periods was required to keep the reporting unit in the data set. The number of observations dropped from the data set at each step of this cleaning process can be found in Appendix A.1.

4.1.2 Business Enterprise Research and Development (BERD) Database

Chapter 1 of this thesis explains the BERD Database in detail, and the discussion here focuses on the aspects of this data set that have not been covered earlier, emphasizing the issues that arise in the match between the ARD data set and BERD long form recipients. Both ARD and BERD contain common identifiers for the reporting units, enterprises and enterprise groups. The sampling ratios for BERD are different from those of ARD, with a larger employment threshold for continuous sampling of reporting units. The sampling fractions for BERD are presented in Table 2.

Table 2: Business Enterprise Research and Development Survey Sampling Fractions

Category	BERD fraction
0-99 employees	0.25
100-399 employees	0.33
400+ employees	All
Largest 400 spenders	All, long form

The R&D information is matched with the ARD at the reporting unit and the enterprise group levels. The BERD micro data set comprises reporting unit level information for all firms identified in various ONS surveys and other sources as performing some R&D (R&D Scoreboard, ABI screening questions and the Community Innovation Surveys are three of the sources used for identifying R&D enterprises). For the unsampled or non-responding reporting units, the ONS imputes the information on R&D variables (such as total intramural R&D, total R&D headcount, breakdowns of current and capital spending, ...) using the average values of these variables in per worker terms for sampled observations within a given product group-size band cell. The main estimation samples used in this study leaves out any group with imputed information, thereby ensuring that the enterprise group level R&D meausures only consist of non-imputed data.

Using these data sets, the production function can be estimated at the reporting unit, enterprise or enterprise group levels. There are also plant-level studies in the literature which use ARD data (for examples, see Harris and Moffat (2011), Harris and Li (2009)), which is possible (although with caveats) when the production function variables are all apportioned to plants using the employment numbers available from the IDBR at the plant level.

Given the distinctions between singleton reporting units and reporting units that are part of larger enterprise groups, imputed and non-imputed BERD information, and long form as opposed to short form respondents in the BERD data set, the estimation of an R&D-augmented production function while correcting for double-counting of inputs requires that I work with multiple sub-samples. In these sub-samples, reporting units which have imputed R&D values have been left out in the calculation of the firm's own R&D spending, for the reasons explained in Chapter 1 of this thesis. All the sub-samples constructed in this study use the continuously sampled ARD manufacturing data set after applying several cleaning steps (See Appendix A.1).

4.2 The estimation sub-samples

Constructing the matched ARD-BERD samples begins with cleaning the ARD manufacturing data set. A detailed description of each cleaning step can be found in Appendix A.1, but in this section, I present a shorter table, outlining the major samples which are important for the discussion here. Before any merges with the BERD data, all the ARD manufacturing observations with missing or zero employment and intermediate inputs, missing capital expenditure information and negative gross output were removed from the data set. If there are gaps between groups of consecutive observations for a reporting unit, then the longest spell of consecutive ARD observations is kept in the data set, while the others have been removed. The number of observations remaining in the data set after the removal of gaps in this way can be seen in the column titled 'continuously sampled and cleaned ARD' in Table 3. Initial observations on each reporting unit drop because beginning-of-period capital values are used. The final two columns in Table 3 relate to the matches with BERD. The penultimate column drops only the reporting units which have imputed R&D, and the final column drops all reporting untis owned by an enterprise group if any member of the group carries imputed information on R&D. Enterprise groups which have no connection to an R&D performing reporting unit have been kept in the data set. Appendix A.1 also provides information on how many reporting units and enterprise groups with some R&D are kept after the steps described in Table 3.

Table 3: Number of observations in the ARD-BERD data sets before and after cleaning

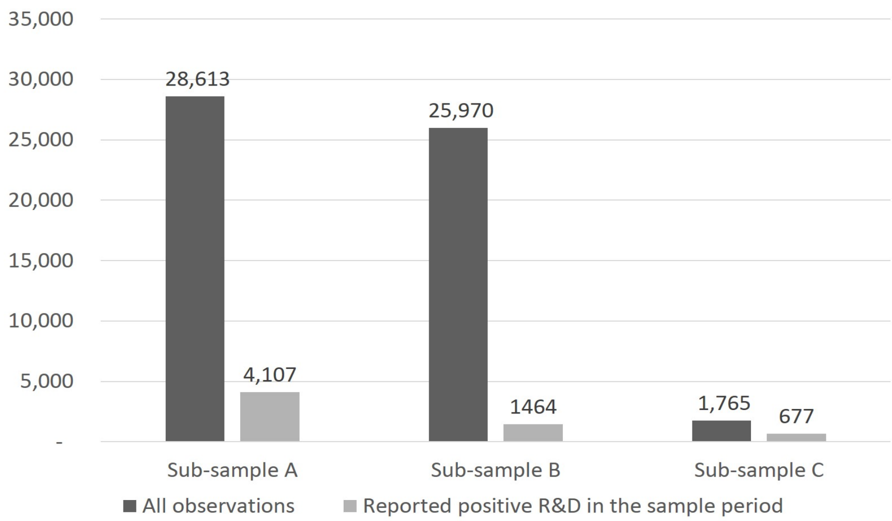
	Sampled ARD manufacturing	Continuously sampled & cleaned ARD	Drop inital obs	Drop imputed R&D rep.units	Drop groups with imputed R&D
1997	12,080	4,711			
1998	12,581	6,185	4,239	3,348	2,682
1999	12,427	6,659	4,325	3,857	3,231
2000	12,250	6,433	4,220	3,562	2,943
2001	12,868	6,539	4,133	3,631	3,043
2002	11,839	6,226	4,298	3,385	2,828
2003	11,576	5,870	4,013	3,417	2,930
2004	11,219	5,443	3,899	3,254	2,785
2005	10,661	4,761	3,361	2,632	2,265
2006	9,619	4,022	2,822	2,126	1,766
2007	7,624	3,309	2,519	1,868	1,549
2008	6,904	1,765	1,594	1,274	1,016
Total	131,648	61,923	39,423	32,354	27,038

Table 3 shows that the number of observations in the main ARD manufacturing data set has decreased sharply over time. This is because of the recent emphasis on service sectors and the resources within ONS being reportedly reallocated to accommodate the sampling of a larger number of service sector firms, at the expense of the manufacturing sample sizes.

Based on the final column of Table 3, I construct three main sub-samples: (a) Sub-sample A: the largest sub-sample, which contains all the reporting units that are members of groups that have no R&D and the members of groups that have non-imputed short and long form R&D, (b) Sub-sample B: the double counting correction sample, which contains all the reporting units that either have only non-imputed long form R&D or no R&D. Short form reporting units are excluded from this sub-sample. (c) Sub-sample C: the smallest sub-sample, which contains all the reporting units which are members of groups that have at least one reporting unit member that is a long form BERD respondent.

The requirements for Sub-sample C are restrictive. Long form responses are required to construct the Jaffe (1986) technology spillover measure, as these are the only observations for which we are able to obtain an 'R&D profile' using the information on fields of R&D activity within a given firm. Attention may be limited to the enterprise group-level R&D, in which case the R&D by any short form respondent or imputed reporting unit member of the group is ignored, considering a 'long form only' measure of enterprise group level R&D that is obtained by adding up all the R&D by long form respondent reporting units of that enterprise group. Sub-sample C additionally drops any short form or imputed BERD reporting units. A more restrictive treatment for Sub-sample C would have been to rule out the whole enterprise group if it has any imputed or short form observations, but this results in too small data sets to offer any external validity. Long form responses amount to around 85 percent of aggregate R&D and a similar share on average at the firm level over the sample period (1997-2008), rendering the zero R&D assumption in Sub-sample C less of a concern. Sample characteristics and comparisons are separately discussed under descriptive statistics later in this section. The number of observations in each of the sub-samples used in the estimations and described here are presented in Figure 1[15].

Figure 1: Number of observations in the estimation sub-samples



4.3 Measures of R&D external to the firm

In the context of spillover measures, the use of imputed values may have some value in reflecting the total technology spillovers or product market rivals' contributions to firms' own productivity. I consider a set of spillover measures, allowing for different treatments of imputed, short form and long form information on R&D.

The source of R&D product field information differs from the manufacturing product field information. The former is sourced by the BERD long form questionnaire, where each reporting unit reports R&D in one or more product fields out of the 33 available. In principle, each long form recipient can report multiple product fields with the amounts of total R&D performed in each of the fields, but in the micro data set very few BERD reporting units report more than a single product field. The product fields are close to two-digit sectors, as I underlined previously in Section 2 (for a list of

[15] In Figure 1, it can be observed that the number of observations in Sub-sample A is slightly larger than shown in the final column of Table 3. This is because the estimation sub-samples use the lagged values of R&D spending. As an example case, when the R&D value for a reporting unit in 2008 is imputed and in 2007 it is non-imputed, the use of the lagged value for R&D allows that the 2008 observation is retained in the estimation samples.

product fields, see Appendix B). At the enterprise group level, each firm may be represented by a vector to summarize the R&D profile of the group, using the 33-element vector X_i, with each element X_{pi} representing the share of the group's total R&D spending in product field p. At the reporting unit level, the R&D profile may again be represented by a similar 1×33 vector, but because almost all reporting units are only assigned a single R&D product field, all elements of the vector will be zero except the field of R&D activity of the reporting unit, which will take on a value of unity (there are a small number of exceptions to this rule, which are dealt with accordingly). The same applies to the enterprise group level measure, except for groups which have two or more long form recipient reporting units. In Sub-sample C, there are 1,036 enterprise groups out of which 309 are multi-unit groups. There is no R&D product field information available for short form and imputed responses (the product field reported in the BERD data for these observations is sourced from the IDBR and refers to their sector of manufacturing activity rather than R&D).

The manufacturing product field information is sourced from the ARD/IDBR local unit data, which provides employment numbers in plants and the local unit's sectoral information at the 5-digit SIC (1992) level. The 5-digit SICs may be grouped to resemble the 33 product fields available for the breakdown of R&D. The equivalent 33-element vector with employment shares in each of the 33 product fields can be called the 'production profile' of a reporting unit or an enterprise group. Production profiles across 33 different manufacturing product fields have been obtained separately at the enterprise group level and the reporting unit level, since the availability of local unit information for both sampled and unsampled ARD units allows for constructing these separate vectors. According to the employment breakdowns, groups operating in multiple product fields are common at both the enterprise group and the reporting unit levels. To illustrate the prevalence of multi-sector groups, Table 4 presents the share of reporting units which belong to groups that have operations in multiple product fields.

Table 4: Share of reporting units in groups with multiple product fields

	Sub-sample A	Sub-sample B	Sub-sample C
Percent	44%	42%	94%
No of obs	28,613	25,970	1,765

Table 4 uses employment shares. The equivalent table with shares of R&D product fields would be meaningful for Sub-sample C only, where the share of reporting units that are members of multi-field R&D enterprise groups is 62 percent.

In the empirical section (Section 5), I use four main measures that reflect R&D external to the firm: (1) weighted sum of all product fields' R&D with weights determined by the production profile of the enterprise group (net of the group's own R&D); (2) weighted sum of all product fields' R&D

with weights determined by the production profile of the reporting unit (net of the reporting unit's own R&D); (3) weighted sum of all R&D external to the firm with weights obtained using production profiles of neighboring firms in product space as in Equation 5 (equivalent to the BSV $SPILLSIC$ measure); (4) weighted sum of all R&D external to the firm with weights obtained using R&D profiles of neighboring firms in technology space (equivalent to the BSV $SPILLTECH$ measure). The fourth measure uses the long form responses in BERD, but the other three measures can also be constructed using the long form only aggregates for comparison purposes (in the analysis using Sub-sample C, long form versions of the other variables have been use for comparability).

4.4 Construction and timing of input measures

The main input variables are capital stock, headcount employment, average wage (as discussed in Section 2), materials and R&D. The timings of these variables are often relevant for the various simultaneity issues frequently discussed in the literature, following Marschak and Andrews (1944). In the cases where a dynamic model or a structural estimation methodology are not used to tackle the simultaneity issue, several authors have used one-period lagged values of all the inputs to address -albeit in a relatively arbitrary fashion- the simultaneous determination of inputs and outputs (for examples, see Hall et al. (2009), Bloom et al. (2013)). In this section, I consider the timings of each input that may be relevant in determining the period t output.

Each of the ARD and BERD survey variables covers the year ending 31 December, which means both the inputs and the output are measured at the end of the year. There are two exceptions to this rule, the first is the headcount employment measure, and the second is the capital stock variable. The headcount employment is sourced by the IDBR (based on PAYE returns), and provides an average of end-of-quarter reports (for the four quarters in the year) for the number of individuals employed in each enterprise. The information from IDBR is then complemented with the ONS Business Registers Employment Survey (BRES)[16]. Given the timing of this variable, it may be plausible to use employment measured contemporaneously with gross output, as the closest employment quantity that enters the output in period t may arguably be the headcount in period t. The double counting correction would then use the BERD long form response for the headcount employment in R&D in period t. An alternative could be to use the period $t-1$ headcount.

The physical capital stock data has been constructed from the investment series, which is a flow variable. In the existing literature, a commonly used methodology to obtain the stock from the flow is the perpetual inventory method, with capital stock following: $K_t = (1-\delta)K_{t-1} + I_t$, where K represents the capital stock, δ represents the depreciation rate and I represents investments in

[16]Special thanks to Christine Woods from the UK Data Service for her support in clarifying various sources of employment information.

physical capital. Assumptions about the initial capital stock of individual firms can be varied and the approach taken in this paper to construct initial values has been summarized in Appendix A.3. The initial value calculation is important both for the firms that existed before the starting period of the data set as they already have some accumulated capital in the beginning period, and also for the new firms that enter the data set after the beginning period, as they will have accumulated some capital before they are sent the ABI form for the first time (Martin (2002)). The aggregate capital stock estimates from the Volume Index of Capital Services (VICS) data set are therefore apportioned in this study to the first observation on each reporting unit in the sample period, according to the unit's share of total intermediate inputs utilized in its two-digit SIC sector[17]. From the second period onwards in the observed lifetime of each reporting unit, the perpetual inventory method is used to quantify their accumulated capital. Given that it is unlikely for all the acquired capital in period t to be fully operational throughout year t, this study uses the beginning of period capital, assuming that it contributes more to the production in the current period.

The timing and construction of the R&D input measure has been an extensively debated issue in the literature, as discussed in detail by Hall et al. (2009) and outlined in Section 2. The main specifications in this paper utilize the flow measure for R&D in the production function which is equivalent to using the stock measure for knowledge under the steady state assumption discussed in Section 2.3. The literature does not have a definitive answer regarding the timing of the R&D variables or the appropriate lag length. There are studies in the literature with static models which use one or more lags (for example, Adams (1990) considers up to 30 lags), as well as those that use current R&D, depending on the available data and the informativeness of each measure in the production process[18].

In Equations 10-12 presented earlier, under the steady state assumption, G_1 is proportional to both R_0 and R_1, and indeed to R&D spending for any other period. If the steady state assumption is reasonable, we should then find similar results using (the natural log of) R_t, R_{t-1}, or R_{t-s} for any s. In Section 5, elasticity estimates with different timings for the R&D variable are explored, suggesting close to no difference between the results and providing evidence to support the steady state approximation.

Double counting-corrections for labor and materials inputs have been possible using the long form respondents' data, by subtracting the R&D-related portions of labor and materials from the totals provided in the ARD. The current R&D headcount, R&D labor cost and R&D materials have been subtracted from traditional headcount, labor cost and materials inputs that are each timed contemporaneously with the output measure. In the main specifications, the R&D input has been

[17]For some sectors, the two-digit SICs have been grouped and the resulting broader sector categorization is called 'SIC letter's by the ONS.

[18]In preliminary work for this study, I considered a set of lags ranging from the first to the fifth lag, including a distributed lag form with all five lags. Only the current value and the first lag appeared to be informative.

timed at $t-1$, as a period t demand shock may affect gross output and R&D spending simultaneously, in which case the use of period t R&D would introduce endogeneity. Regarding the labor quality adjustment that is included in the regressions as labor costs per worker (average wages), it has been possible to use the information on salaries of R&D employees, subtract this amount from the total labor cost and find an average wage measure for non-R&D employment using the non-R&D employment described here.

I apply the inverse hyperbolic sine transform (Burbidge et al. (1988)) on all the input and output variables, which allows for the inclusion of zero R&D observations in the estimation samples which would not have been possible using the log transform. I demonstrate in Section 5 that the results from two estimations on the same sample which use the natural logarithms of variables and the inverse hyperbolic sine transformations are the same up to the third decimal point for both coefficient estimates and standard errors. The transformation of variable z takes the form $sinh^{-1}z = ln(z + \sqrt{z^2+1})$, which has a similar shape to the log transform.

4.5 Descriptive statistics

The ARD continuously sampled manufacturing reporting units provide the basis for the sub-samples used in the regressions[19]. The average cost shares of materials, labor and capital can be instructive about the elasticity of output with respect to these inputs, especially if constant returns to scale is a plausible assumption for the given sample of firms. In the ARD sample, on average, input cost shares in gross output in a typical period are around 60 percent for materials, 25 percent for labor and 15 percent for physical capital. The behavior of these cost share measures is very stable over the time period observed in our regression samples. The cross-sectoral variation is also not very large at this aggregate level, across both positive R&D and production-only reporting units. These ratios are close to the findings in the existing literature and growth accounting exercises.

Long form responses constitute around 85 percent of the total value of R&D spending in BERD, which includes short form responses and imputed data. This means that despite the much smaller number of reporting units that receive the long form questionnaire in the sample frame of BERD, the coverage of total R&D value is sizable (for example in year 2000, more than 400 long form reporting units per period compared with a total of more than 9,000 short form and imputed responses).

There are three main sub-samples of interest for the production function exercise with the enterprise group or reporting unit's own and external R&D as inputs. The characteristics of Sub-sample A and Sub-sample B are very similar, whereas Sub-sample C, where locations of R&D expenditure in

[19]Over the years, the ONS increased the coverage of the ARD data set, collecting data from firms in a larger number of sectors and increasing the representation of services sector reporting units. This came at the expense of the number of reporting units in manufacturing sub-sectors, which is especially pronounced in the data for 2008 and later in the Annual Business Survey.

technology space and the related technology spillovers can be determined, is composed of reporting units and enterprise groups that are larger in size, that perform considerably more R&D and that have a larger share of observations in high technology sectors.

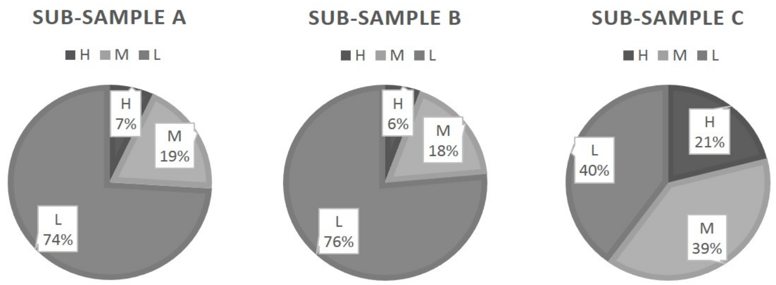
Table 5 presents summary statistics on gross output and employment across the three sub-samples, providing evidence for the similarities between the large Sub-sample A and the sub-sample on which the double-counting correction can be performed (Sub-sample B). The coverage of total gross output are similar for Sub-samples A and B, while Sub-sample A covers a considerably higher share of total employment. The long form sub-sample (C) covers roughly 20 percent of the total gross output and total employment covered by Sub-sample A, but the employment headcount in an average reporting unit is much higher above 700, whereas an average reporting unit in Sub-sample A only has 220 employees.

Table 5: Gross output and employment in different sub-samples

	Gross output (in 1997 prices)			Employment			
Sample	Total	Mean	St.dev.	Total	Mean	St.dev.	Freq.
Sub-sample A	701,486,165	24,516	47,661	6,285,224	220	373	28,613
Sub-sample B	554,273,314	21,343	44,345	5,025,243	194	349	25,970
Sub-sample C	171,223,259	97,010	90,362	1,249,811	708	688	1,765

In terms of sector distributions, Figure 2 shows that sub-samples A and B appear very similar when a broad sector grouping into high (H), medium (M) and low (L) technology sectors is considered. The allocation of product fields into H, M and L technology sectors follow the same classification as the one used in Chapter 1 of this thesis. This is reassuring for the double-counting correction sub-sample, but it also provides evidence that the small sample on which we can quantify technology spillovers using the Jaffe (1986) methodology is not representative of the overall manufacturing sector.

Figure 2: Distribution of reporting units across high, medium, low technology sectors



Finally, amounts of R&D external to each firm can be calculated in the different ways described in Section 4.1.2. For each reporting unit, summary statistics for the different measures of external R&D are presented in Table 6. The first column of Table 6 presents the mean and standard deviation of the basic aggregate spillover measures, which are constructed as weighted sums as described earlier, including all the imputed and non-imputed R&D in the relevant sectors. Mean and standard deviation of product market proximity measures presented under the heading 'Jaffe (1986) product market' in Table 6 use both the imputed and non-imputed R&D, with the weights from employment shares in each of the manufacturing product fields in which the firm operates. The final columns present the mean and standard deviation of the technology spillover measure, which appear larger on average than most of the other measures discussed, but this is because the sample on which this measure can be calculated requires that at least one long form recipient exists within the enterprise group.

Table 6: Summary statistics on proximity measures, constant (1997) thousand GBP

Measures with enterprise group level weights:

	Aggregate measure		Jaffe (1986) product market weights		Jaffe (1986) tech. distance weights	
	Mean	St.dev	Mean	St.dev	Mean	St.dev
Sub-sample A	195,274	225,458	414,485	440,737	-	-
Sub-sample B	184,093	219,879	400,762	428,224	-	-
Sub-sample C	320,031	225,246	702,729	542,693	757,094	732,158

Measures with reporting unit level weights:

	Aggregate measure		Jaffe (1986) product market weights		Jaffe (1986) tech. distance weights	
	Mean	St.dev	Mean	St.dev	Mean	St.dev
Sub-sample A	187,357	234,856	22,292	96,398	-	-
Sub-sample B	175,749	229,023	18,799	90,204	-	-
Sub-sample C	297,445	271,012	213,549	219,958	275,413	582,535

In Sub-sample C, where both the technology spillovers and product market competition effects using the Jaffe (1986) weights at the enterprise group level can be calculated (top panel of Table 6), the correlation between the two measures is around 0.5, which is slightly higher than the finding of BSV, but the correlation is low enough, suggesting that the two effects may be separately identified in the empirical analysis. In the same sample, the correlation between the Jaffe enterprise group level technology spillover measure and the crude sector aggregate calculated as the weighted sum with the production profile at the group level as weights is lower, at 0.37. The Jaffe weights using the production profiles of groups on Sub-sample B appear to have a correlation with the crude sector aggregate measures with correlation coefficients around 0.35, which is also in the same ballpark when reporting unit level weights instead of group level weights are considered to construct the measures.

5 Results

5.1 Basic specification

The empirical model for the baseline three-factor production function is the Cobb-Douglas specification provided in Section 2. In this general model, the error terms ϵ_{it} may be correlated with the input variables and split into the following components: year dummies τ_t, to capture common shocks that affect all firms in the same year; firm fixed effects η_i, to capture permanent firm-level heterogeneity; firm-specific error terms ν_{it} which capture productivity shocks that are specific to the firm and the time period:

$$y_{it} = a + \beta_k k_{it} + \beta_l l_{it} + \beta_m m_{it} + \eta_i + \tau_t + \nu_{it} \tag{13}$$

Subscripts i and t represent reporting units and years respectively. k, l, m are the inverse hyperbolic sine transforms of capital, labor and intermediate inputs; y is the output measure. Input coefficients β_k, β_l and β_m yield elasticities of output with respect to these inputs. The constant term is the average total factor productivity (TFP) over all the firm-years in the sample.

All the regression tables presented in this section include year dummy variables, their interactions with product fields and use standard errors clustered at the reporting unit level[20]. All the tables contain two sets of estimates on each of these sub-samples, one set of ordinary least squares (OLS) regression results and one set with the within-groups transformation with reporting unit fixed effects (FE).

Table 7 shows the results from basic production function estimation without R&D using Sub-sample A, which is the largest sub-sample. The left hand panel of Table 7 uses the inverse hyperbolic sine transformed versions of the input and output variables, and the right hand panel uses the natural logarithm (log) transformation. A time-invariant indicator variable has been included to capture whether the reporting unit itself performs any R&D (the dummy takes the value unity if the reporting unit has ever reported any R&D and zero otherwise). The table demonstrates that the two transformations yield very similar results up to the third decimal point when all the input and output variables take positive values. The inverse hyperbolic sine transformation allows for zeros, which is an advantage as it enables the use of the information on reporting units which do not themselves have R&D operations in the regressions that include R&D variables.

Elasticity estimates reported in Columns (OLS1a) and (FE1a) of Table 7 are in the same ballpark as generally found in the literature for the manufacturing sector, and close to the cost shares presented in the previous section, with OLS estimates of the elasticity of output with respect to intermediate inputs around 62 percent and with respect to headcount labor around 28 percent (Columns (OLS1a) and (OLS1b)). As typically observed in the literature, the coefficient on capital drops as we move from OLS to FE results, but it is still positive and highly significant with a magnitude of around 6 percent in FE results. In fact, the coefficients on headcount labor and intermediate inputs also drop in the FE

[20]To account for the contemporaneous correlation between the members of the same group at the same time period, two way clustering has also been used in regressions not presented in this paper. The results were similar and the conclusions from hypothesis tests reported in this did not change when two way clustering was applied.

results. While OLS estimates in Columns (OLS1a) and (OLS1b) are close to constant returns to scale (CRS)[21], the corresponding FE results in Columns (FE1a) and (FE1b) seem to reject CRS in favor of decreasing returns. In Columns (OLS2a) and (FE2a), the inverse hyperbolic sine transform of the average wage is included in the regression as a quality adjustment for the labor input. This increases the magnitude of the coefficient on the labor input, with the elasticity with respect to the headcount measure going up by about 10 percentage points, and the coefficients on headcount labor and average wages being very close in magnitude to each other. When the average wage variable is omitted, its effect seems to have been captured by the materials and capital inputs and the R&D indicator.

Table 8 introduces the amount of R&D performed at: (i) the enterprise group level in the left hand panel, similar to the specification used in Adams and Jaffe (1996), and (ii) the reporting unit level in the right hand panel, as in most of the previous studies that used the UK BERD-ARD matched data sets. The addition of the R&D input as a factor of production to the basic specification in Equation 13 becomes the following, with the β_r coefficient estimates capturing the partial contribution of R&D expenditures in total output:

$$y_{it} = a + \beta_k k_{it} + \beta_l l_{it} + \beta_m m_{it} + \beta_r r_{it} + \eta_i + \tau_t + \nu_{it} \tag{14}$$

Table 7: Baseline static regression results, Sub-sample A

	Inverse hyperbolic sine transform				Natural logarithm transform			
	OLS1a	FE1a	OLS2a	FE2a	OLS1b	FE1b	OLS2b	FE2b
Labor	0.277***	0.190***	0.371***	0.414***	0.277***	0.190***	0.370***	0.414***
	(0.004)	(0.014)	(0.004)	(0.017)	(0.004)	(0.014)	(0.004)	(0.017)
Materials	0.618***	0.547***	0.539***	0.454***	0.618***	0.547***	0.539***	0.454***
	(0.006)	(0.016)	(0.006)	(0.015)	(0.006)	(0.016)	(0.006)	(0.015)
Capital	0.102***	0.058***	0.079***	0.031**	0.102***	0.058***	0.079***	0.031**
	(0.006)	(0.015)	(0.005)	(0.013)	(0.006)	(0.015)	(0.005)	(0.013)
R&D dummy	0.031***	.	0.009	.	0.031***	.	0.009	.
	(0.007)	.	(0.007)	.	(0.007)	.	(0.007)	.
Average wage			0.382***	0.365***			0.379***	0.364***
			(0.006)	(0.018)			(0.006)	(0.018)
Year effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Sector-year eff.	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
R_squared	0.979	0.695	0.985	0.757	0.979	0.695	0.985	0.757
No of total obs	28,613	28,613	28,613	28,613	28,613	28,613	28,613	28,613
No of R&D RU	4,107	4,107	4,107	4,107	4,107	4,107	4,107	4,107

Standard errors clustered at the reporting unit level are in parantheses below the coefficient.
'No of R&D RU' stands for the number of observations on reporting units that have ever had positive R&D at the reporting unit level.

With the inclusion of the R&D variable (one period lagged in all regressions), the difference between Columns (OLS3a) and (OLS4a) for the specifications which use the enterprise group level R&D and between Columns (OLS3b) and (OLS4b) for the specifications which use the reporting unit level R&D becomes clear: the omission of the average wage variable as a proxy for labor quality seems to cause the variable which represents the amount of R&D to partly pick up the effect of labor quality. When the average wage variable is included, the magnitudes of the point estimates on R&D elasticity

[21] Formal tests of the CRS restriction $\beta_k + \beta_l + \beta_m = 1$ are not rejected in the OLS regressions.

Table 8: Static specification with R&D flow as input, Sub-sample A

	R&D at enterprise group level:				R&D at reporting unit level:			
	OLS3a	FE3a	OLS4a	FE4a	OLS3b	FE3b	OLS4b	FE4b
Labor	0.276***	0.189***	0.370***	0.414***	0.277***	0.189***	0.370***	0.414***
	(0.004)	(0.014)	(0.004)	(0.017)	(0.004)	(0.014)	(0.004)	(0.017)
Materials	0.619***	0.547***	0.540***	0.454***	0.619***	0.547***	0.540***	0.454***
	(0.006)	(0.016)	(0.006)	(0.015)	(0.006)	(0.016)	(0.006)	(0.015)
Capital	0.100***	0.058***	0.078***	0.031**	0.101***	0.058***	0.079***	0.031**
	(0.006)	(0.015)	(0.005)	(0.013)	(0.006)	(0.015)	(0.005)	(0.013)
R&D dummy	0.001	.	(0.011)	.	-0.001	.	-0.008	.
	(0.009)	.	(0.008)	.	(0.011)	.	(0.009)	.
R&D amount	0.008***	0.001	0.005***	0.000	0.007***	0.001	0.004**	0.000
	(0.001)	(0.001)	(0.001)	(0.001)	(0.002)	(0.002)	(0.002)	(0.002)
Average wage			0.380***	0.365***			0.381***	0.365***
			(0.006)	(0.018)			(0.006)	(0.018)
Year effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Sector-year eff.	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
R_squared	0.979	0.695	0.985	0.757	0.979	0.695	0.985	0.757
No of total obs	28,613	28,613	28,613	28,613	28,613	28,613	28,613	28,613
No of R&D RU	4,107	4,107	4,107	4,107	4,107	4,107	4,107	4,107

Standard errors clustered at the reporting unit level are in parantheses below the coefficient.
The inverse hyperbolic sine transformation is applied to all variables except binary dummies.
'No of R&D RU' stands for the number of observations on reporting units that have ever had positive R&D at the reporting unit level.

are approximately halved. The coefficients on materials and capital are also possibly estimated with an upward bias in the regressions which omit the average wage variable. The inclusion of a proxy for labor quality is in line with the theoretical foundation in Griliches (1979), who argues that the omission of such a variable causes the labor input to be mis-measured. UK studies which use BERD-ARD matched data sets that were cited earlier in this paper do not include a labor quality adjustment, which is one of the reasons for the larger magnitudes of R&D coefficient estimates found in these studies. In the OLS regressions presented in Table 8, the magnitudes of the point estimates for the R&D elasticity are a modest 0.3-0.4 percent (Columns (OLS4a) and (OLS4b)) and not significantly different from zero when reporting unit fixed effects are included. A prominent feature of R&D data is the low variation in the time dimension, which also characterizes the data set used in this study. The inclusion of reporting unit fixed effects most of the time completely wipes out the effect of the R&D input, in the specifications where the mis-measurement in labor and materials inputs are not corrected for by removing the R&D components of these variables.

The convention in the literature is to apply the log transformation, which necessitates dropping observations on reporting units with zero R&D. Other simple transformations have also been used to overcome this problem, such as adding '1' to the R&D amount (See, for example, Harris et al. (2009)). Table 7 demonstrated the equivalence of the results from regressions which use variables that are transformed using the log and the inverse hyperbolic sine transform. In the presence of the R&D variable, the coefficient estimates, standard errors and R_squared values are identical in the two transformations up to the third decimal point[22].

Table 9 additionally demonstrates the consequences of focusing only on observations with positive

[22]The version of Table 9 with log transforms of variables is available upon request.

R&D values for the magnitudes of the elasticity estimates. In Columns (OLS6a) and (OLS6b) (or equivalently (OLS8a) and (OLS8b)), the coefficient on R&D is larger in magnitude than the estimates reported in Table 8 which used larger data sets and incorporated the information from an R&D-doing reporting unit both when it reports positive R&D as well as when it reports zero R&D. The comparison between Tables 8 and 9 also suggests that the coefficients on labor and materials may be different for reporting units with positive R&D and the reporting units with zero R&D. I will explore heterogeneity in all input coefficients across reporting units with zero R&D and those with positive R&D in later specifications in this section.

Table 9: Static specification with R&D flow as input, Sub-sample A positive R&D observations

	R&D at enterprise group level:				R&D at reporting unit level:			
	OLS7a	FE7a	OLS8a	FE8a	OLS7b	FE7b	OLS8b	FE8b
Labor	0.216***	0.202***	0.319***	0.381***	0.217***	0.203***	0.319***	0.383***
	(0.013)	(0.038)	(0.014)	(0.050)	(0.013)	(0.038)	(0.014)	(0.050)
Materials	0.642***	0.602***	0.584***	0.533***	0.642***	0.602***	0.584***	0.532***
	(0.018)	(0.036)	(0.017)	(0.037)	(0.017)	(0.036)	(0.017)	(0.037)
Capital	0.122***	0.112***	0.089***	0.078**	0.121***	0.112***	0.088***	0.078**
	(0.015)	(0.037)	(0.014)	(0.032)	(0.015)	(0.037)	(0.014)	(0.033)
R&D amount	0.026***	-0.003	0.009**	-0.008	0.029***	-0.005	0.010**	-0.01
	(0.004)	(0.007)	(0.004)	(0.007)	(0.005)	(0.009)	(0.005)	(0.008)
Average wage			0.369***	0.311***			0.368***	0.312***
			(0.026)	(0.057)			(0.026)	(0.057)
Year effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Sector-year eff.	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
R_squared	0.973	0.747	0.978	0.775	0.973	0.747	0.978	0.776
No of total obs	3,005	3,005	3,005	3,005	3,005	3,005	3,005	3,005
No of R&D RU	3,005	3,005	3,005	3,005	3,005	3,005	3,005	3,005

Standard errors clustered at the reporting unit level are in parantheses below the coefficient.
All variables transformed using the inverse hyperbolic sine transform.
Natural log transform produces results that are the same up to the third decimal point.
'No of R&D RU' stands for the number of observations on reporting units that have ever had positive R&D at the reporting unit level.

5.2 Correcting mis-measurement in labor and materials

So far, the impact of own R&D on productivity appears to have been very modest, either when measured in terms of the total R&D done by the parent firm or in terms of the reporting unit's own R&D. Now, in Table 10, labor and materials input measures are corrected to address the mis-measurement issue by subtracting the R&D component of headcount labor and materials from the total headcount and materials of the reporting unit. I was able to carry out this correction thanks to the availability of BERD long form breakdowns of R&D into labor costs and other current expenditure. The availability of the labor cost variables in both ARD and BERD also allowed me to distinguish between R&D salaries and overall salaries reported in ARD, constructing a 'non-R&D average wage' variable. It is common in the literature to call this correction the 'double counting correction', although it is a way of addressing a mis-measurement problem with the standard production inputs. I will nevertheless follow the convention in the literature in the rest of this paper and refer to the operation as the ‘double counting correction’. Short form recipient R&D reporting units are now dropped from the sample, yielding Sub-sample B as described in Section 4.

There is a substantial effect of the double counting correction on the R&D elasticity estimates, both when own R&D refers to reporting unit level R&D and when it refers to enterprise group level R&D. Table 11 follows Table 10 for comparison purposes, as Table 11 is based on the same sample as in Table 10 but uses the uncorrected measures of labor and materials. Given the importance of the inclusion of the average wage variable as discussed earlier, I emphasize the results from the regressions which include this variable from now on. In Column (OLS10a) in Table 10, the R&D elasticity estimate is highly significant and has a magnitude of 1 percent, compared with the 0.6 percent reported in Column (OLS12a) of Table 11 using the enterprise group level R&D measure. When reporting unit fixed effects are included in this specification, there does not appear to be a notable improvement in the magnitude and significance of the R&D elasticity estimates reported in Column (FE10a) compared with those in Column (FE12a).

In the right hand panels of Tables 10 and 11, the coefficient on own R&D of the reporting unit is now estimated in the OLS regression as 2.1 percent and highly significant in Table 10, and this magnitude is more than three times as large as the 0.6 percent reported in Table 11. Even the FE results presented in Column (FE10b) seem to be much larger in magnitude (1.3 percent) than their counterparts that were estimated using input measures that are not corrected for double counting (0.1 percent in Column (FE12b)), despite lacking statistical significance at the 10 percent level. In the tables that follow after Table 11, headcount labor, average wage and materials are corrected for double counting unless stated otherwise in the table footnotes.

The comparison between Tables 10 and 11 does not reveal a notable change in the estimates of the elasticity of output with respect to the headcount labor and materials. The estimated coefficient on average wage, which is corrected using the salary information in BERD for scientists and researchers, decreased from 38 percent to 36 percent after the double counting correction in Table 10.

5.3 Exploring heterogeneities across R&D and production units

A potential source of heterogeneity in the estimates of R&D and other input elasticities may be the distinction between R&D-doing reporting units and other reporting units which have not had any R&D operation during the sample period. The latter group can be thought of as ‘production-only’ reporting units as they are in the sample because of having been captured in the manufacturing ARD survey only. By showing that the positive R&D reporting units may take on different input elasticities than the pooled sample, Table 9 has already demonstrated that we may expect estimated input coefficients to be different between these two types of reporting units. Table 12 explores the presence of such heterogeneity across R&D and production-only reporting units. In Table 12, each

Table 10: Sub-sample B, with double counting correction in labor and materials

	R&D at enterprise group level:				R&D at reporting unit level:			
	OLS9a	FE9a	OLS10a	FE10a	OLS9b	FE9b	OLS10b	FE10b
Non-R&D labor	0.277***	0.178***	0.365***	0.379***	0.278***	0.178***	0.367***	0.380***
	(0.005)	(0.016)	(0.005)	(0.032)	(0.004)	(0.015)	(0.005)	(0.032)
Non-R&D materials	0.615***	0.537***	0.537***	0.454***	0.615***	0.538***	0.538***	0.454***
	(0.007)	(0.018)	(0.006)	(0.019)	(0.007)	(0.018)	(0.006)	(0.019)
Capital	0.101***	0.058***	0.083***	0.036**	0.102***	0.057***	0.083***	0.035**
	(0.007)	(0.016)	(0.006)	(0.015)	(0.007)	(0.016)	(0.006)	(0.015)
R&D dummy	0.056***	.	0.042***	.	0.028**	.	0.016*	.
	(0.011)	.	(0.010)	.	(0.011)	.	(0.009)	.
R&D amount	0.012***	0.001	0.010***	0.001	0.024***	0.011	0.021***	0.013
	(0.001)	(0.002)	(0.001)	(0.002)	(0.003)	(0.010)	(0.003)	(0.010)
Non-R&D av. wage			0.359***	0.314***			0.359***	0.315***
			(0.012)	(0.051)			(0.012)	(0.051)
Year effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Sector-year eff.	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
R_squared	0.978	0.687	0.984	0.742	0.978	0.687	0.984	0.743
No of total obs	25,970	25,970	25,970	25,970	25,970	25,970	25,970	25,970
No of R&D RU	1,464	1,464	1,464	1,464	1,464	1,464	1,464	1,464

Standard errors clustered at the reporting unit level are in parantheses below the coefficient.
'No of R&D RU' stands for the number of observations on reporting units that have ever had positive R&D at the reporting unit level.
The inverse hyperbolic sine transformation is applied to all variables except binary dummies.

Table 11: Sub-sample B, inputs not corrected for double counting

	R&D at enterprise group level:				R&D at reporting unit level:			
	OLS11a	FE11a	OLS12a	FE12a	OLS11b	FE11b	OLS12b	FE12b
Labor	0.278***	0.180***	0.372***	0.410***	0.279***	0.180***	0.373***	0.410***
	(0.004)	(0.016)	(0.004)	(0.019)	(0.004)	(0.016)	(0.004)	(0.019)
Materials	0.618***	0.543***	0.537***	0.449***	0.617***	0.543***	0.537***	0.449***
	(0.007)	(0.018)	(0.006)	(0.017)	(0.007)	(0.018)	(0.006)	(0.017)
Capital	0.097***	0.053***	0.077***	0.028*	0.099***	0.053***	0.079***	0.027*
	(0.007)	(0.016)	(0.006)	(0.014)	(0.007)	(0.016)	(0.006)	(0.014)
R&D dummy	0.038***	.	0.015*	.	0.028***	.	0.012	.
	(0.010)	.	(0.009)	.	(0.011)	.	(0.009)	.
R&D amount	0.009***	0.001	0.006***	0.000	0.012***	0.003	0.006**	0.003
	(0.001)	(0.002)	(0.001)	(0.002)	(0.003)	(0.007)	(0.003)	(0.007)
Average wage			0.380***	0.366***			0.380***	0.366***
			(0.006)	(0.020)			(0.006)	(0.020)
Year effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Sector-year eff.	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
R_squared	0.978	0.691	0.984	0.757	0.978	0.691	0.984	0.757
No of total obs	25,970	25,970	25,970	25,970	25,970	25,970	25,970	25,970
No of R&D RU	1,464	1,464	1,464	1,464	1,464	1,464	1,464	1,464

Standard errors clustered at the reporting unit level are in parantheses below the coefficient.
'No of R&D RU' stands for the number of observations on reporting units that have ever had positive R&D at the reporting unit level.
The inverse hyperbolic sine transformation is applied to all variables except binary dummies.

input coefficient is allowed to take on different values for reporting units which have had positive R&D in at least one year during the sample period. The input coefficients are interacted with the time-invariant R&D dummy to capture the elasticities for the reporting units which had any R&D operation during the sample period. The elasticity estimates for production-only reporting units are captured by the interaction 'No-R&D dum.' (equal to 1-R&D dummy). At the bottom of the table, p-values for the hypothesis tests of equal coefficients on each of the traditional inputs headcount labor, materials and capital, as well as that of the own R&D variable are presented. These suggest that the two groups (R&D and No-R&D reporting units) may have different elasticities of output with respect to headcount labor, materials and own R&D.

As before, the right hand panel of Table 12 takes the reporting unit level R&D as the measure of the reporting unit's own R&D, whereas the left hand panel takes enterprise group level R&D to capture the effect of own R&D on a reporting unit's productivity[23]. The specification which uses reporting unit-level R&D (right hand panel of Tables 8-12) imposes the restriction that reporting units which report zero R&D in a particular year derive no benefit from R&D performed elsewhere in the same enterprise group. The positive and significant coefficient on the own R&D input at the enterprise group level in Columns (OLS13a) and (OLS14a) of Table 12 provides evidence for the productivity effects of R&D on reporting units which themselves do not perform R&D activity.

The comparison between Tables 12 and 13 now also demonstrates a change in the coefficient on headcount labor when the inputs are corrected for double counting. In table 13, the coefficient on the uncorrected headcount labor input is estimated by OLS to be 34 percent for the positive R&D reporting units (Columns (OLS16a) and (OLS16b)), whereas when the inputs are corrected for double counting, the magnitude of this estimate drops to 28 percent (Columns (OLS14a) and (OLS14b)). The correction does not have an effect on the input elasticity estimates for the production-only reporting units. We also do not observe a large change in the estimated elasticity of output with respect to materials. As before, the effect on the OLS coefficient on R&D input is pronounced, with the elasticity of output with respect to own R&D at the enteprise group level estimated to be 0.4 percent without the double counting correction and 2 percent with the correction. For production-only units, the elasticity of output with respect to R&D done at the group level estimated by OLS is positive and significant, with a magnitude of 0.6 percent with or without the correction. The right hand panels of Tables 12 and 13 show that the double counting correction increases the estimated productivity effect of the reporting unit's own R&D from an insignificant 0.5 percent to 2.3 percent and significant at the 1 percent level. The FE estimates for the coefficient on own R&D also increase in magnitude but they are not significant at the 10 percent level even after the double counting correction.

Earlier in Table 9, there was a noticeable drop in the total number of observations from the number of observations on R&D-doing reporting units that was reported in the earlier Tables 7 and 8. This is because the time-invariant R&D dummy variable takes a value of unity even in the years before the reporting unit begins its R&D operation, or in the years where it does not report positive R&D. In the samples, around half of the observations on reporting units with positive R&D continuously report positive R&D, and more than a quarter begin their R&D operations during the sample period. The remaining observations are on reporting units which either stop reporting positive R&D after a certain year in the sample or follow a 'stop-and-go' pattern.

Regarding the steady state assumption exploited here to use the R&D flow instead of the stock variable, the reporting units which continuously report positive R&D may be thought of as the best

[23]The coefficient on R&D for the production-only reporting units drops in the right hand panel, as all production-only reporting units always report zero R&D.

Table 12: Sub-sample B, inputs allowed to vary across positive R&D reporting units and production-only units, labor and materials corrected for double counting

	R&D at enterprise group level:				R&D at reporting unit level:			
	OLS13a	FE13a	OLS14a	FE14a	OLS13b	FE13b	OLS14b	FE14b
L*R&D dum.	0.221***	0.149***	0.278***	0.184***	0.222***	0.152***	0.278***	0.188***
	(0.019)	(0.045)	(0.028)	(0.070)	(0.019)	(0.044)	(0.027)	(0.070)
L*No-R&D dum.	0.280***	0.179***	0.370***	0.413***	0.281***	0.179***	0.371***	0.413***
	(0.005)	(0.016)	(0.004)	(0.019)	(0.005)	(0.016)	(0.004)	(0.019)
M*R&D dum.	0.638***	0.470***	0.581***	0.461***	0.638***	0.474***	0.583***	0.464***
	(0.023)	(0.059)	(0.023)	(0.060)	(0.023)	(0.057)	(0.023)	(0.058)
M*No-R&D dum.	0.614***	0.543***	0.536***	0.447***	0.614***	0.543***	0.535***	0.447***
	(0.007)	(0.019)	(0.006)	(0.017)	(0.007)	(0.019)	(0.006)	(0.017)
K*R&D dum.	0.118***	0.160***	0.113***	0.134***	0.117***	0.153***	0.112***	0.127***
	(0.018)	(0.044)	(0.021)	(0.044)	(0.018)	(0.043)	(0.020)	(0.042)
K*No-R&D dum.	0.099***	0.046***	0.081***	0.023	0.101***	0.046***	0.082***	0.023
	(0.007)	(0.017)	(0.006)	(0.015)	(0.007)	(0.017)	(0.006)	(0.015)
R*R&D dum.	0.021***	0.005	0.020***	0.004	0.023***	0.009	0.023***	0.009
	(0.003)	(0.006)	(0.003)	(0.006)	(0.003)	(0.009)	(0.004)	(0.009)
R*No-R&D dum.	0.008***	0.000	0.006***	0.000	.	.	.	.
	(0.001)	(0.002)	(0.001)	(0.002)	.	.	.	.
R&D dummy	-0.029	.	0.437	.	-0.016	.	0.459*	.
	(0.087)	.	(0.267)	.	(0.086)	.	(0.260)	.
W*R&D dum.			0.192**	0.033			0.188**	0.035
			(0.088)	(0.092)			(0.086)	(0.093)
W*No-R&D dum.			0.370***	0.371***			0.371***	0.371***
			(0.009)	(0.020)			(0.009)	(0.020)
Year effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Sector-year eff.	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
R_squared	0.978	0.688	0.984	0.752	0.978	0.688	0.984	0.753
No of total obs	25,970	25,970	25,970	25,970	25,970	25,970	25,970	25,970
No of R&D RU	1,464	1,464	1,464	1,464	1,464	1,464	1,464	1,464
p-val., equal β_L	0.002	0.535	0.001	0.001	0.002	0.562	0.001	0.002
p-val., equal β_M	0.329	0.235	0.055	0.818	0.296	0.24	0.041	0.775
p-val., equal β_K	0.309	0.015	0.115	0.015	0.372	0.019	0.133	0.018
p-val., equal β_R	0.000	0.488	0.000	0.415	.	.	.	.

Headcount labor (L), materials (M) and average wage (W) variables are corrected for double counting. Physical capital (K) is not.
Standard errors clustered at the reporting unit level are in parantheses below the coefficient.
'No of R&D RU' stands for the number of observations on reporting units that have ever had positive R&D at the reporting unit level.
The inverse hyperbolic sine transformation is applied to all variables except binary dummies.

Table 13: Sub-sample B, inputs allowed to vary across positive R&D reporting units and production-only units, inputs not corrected for double counting

	R&D at enterprise group level:				R&D at reporting unit level:			
	OLS15a	FE15a	OLS16a	FE16a	OLS15b	FE15b	OLS16b	FE16b
L*R&D dum.	0.234***	0.175***	0.337***	0.326***	0.234***	0.175***	0.336***	0.326***
	(0.016)	(0.046)	(0.016)	(0.066)	(0.016)	(0.046)	(0.016)	(0.066)
L*No-R&D dum.	0.281***	0.179***	0.373***	0.415***	0.282***	0.179***	0.374***	0.415***
	(0.005)	(0.016)	(0.004)	(0.019)	(0.005)	(0.016)	(0.004)	(0.019)
M*R&D dum.	0.662***	0.536***	0.580***	0.485***	0.662***	0.536***	0.581***	0.486***
	(0.020)	(0.056)	(0.019)	(0.058)	(0.020)	(0.056)	(0.019)	(0.058)
M*No-R&D dum.	0.615***	0.543***	0.535***	0.446***	0.615***	0.543***	0.535***	0.446***
	(0.007)	(0.019)	(0.006)	(0.017)	(0.007)	(0.019)	(0.006)	(0.017)
K*R&D dum.	0.093***	0.110***	0.073***	0.078**	0.094***	0.109***	0.073***	0.077**
	(0.016)	(0.040)	(0.014)	(0.039)	(0.016)	(0.041)	(0.014)	(0.039)
K*No-R&D dum.	0.098***	0.046***	0.078***	0.022	0.100***	0.046***	0.079***	0.022
	(0.007)	(0.017)	(0.006)	(0.015)	(0.007)	(0.017)	(0.006)	(0.015)
R*R&D dum.	0.010***	0.001	0.004*	0.001	0.011***	0.001	0.005	0.002
	(0.002)	(0.006)	(0.002)	(0.005)	(0.003)	(0.007)	(0.003)	(0.007)
R*No-R&D dum.	0.008***	0.000	0.006***	0.000	.	.	.	.
	(0.001)	(0.002)	(0.001)	(0.002)	.	.	.	.
R&D dummy	-0.109	.	-0.197*	.	-0.099	.	-0.181*	.
	(0.083)	.	(0.101)	.	(0.083)	.	(0.101)	.
W*R&D dum.			0.388***	0.244***			0.385***	0.244***
			(0.028)	(0.071)			(0.029)	(0.070)
W*No-R&D dum.			0.379***	0.374***			0.380***	0.374***
			(0.006)	(0.020)			(0.006)	(0.020)
Year effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Sector-year eff.	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
R_squared	0.978	0.691	0.984	0.758	0.978	0.691	0.984	0.758
No of total obs	25,970	25,970	25,970	25,970	25,970	25,970	25,970	25,970
No of R&D RU	1,464	1,464	1,464	1,464	1,464	1,464	1,464	1,464
p-val., equal β_L	0.005	0.927	0.027	0.188	0.004	0.930	0.021	0.191
p-val., equal β_M	0.020	0.897	0.021	0.513	0.019	0.901	0.019	0.508
p-val., equal β_K	0.747	0.140	0.689	0.170	0.703	0.149	0.660	0.178
p-val., equal β_R	0.423	0.877	0.481	0.825	0.000	0.837	0.101	0.789

Inputs headcount labor (L), materials (M), physical capital (K) and average wage (W) are not corrected for double counting.
Standard errors clustered at the reporting unit level are in parantheses below the coefficient.
'No of R&D RU' stands for the number of observations on reporting units that have ever had positive R&D at the reporting unit level.
The inverse hyperbolic sine transformation is applied to all variables except binary dummies.

suited group for such approximation to apply. The stop-and-go pattern may undermine the steady state approximation, although such reporting units constitute a small portion of the sample, with observations on reporting units that follow a stop-and-go pattern constituting fewer than 10 percent of the observations labeled as having ever performed R&D. Reporting units which sometimes report zero R&D may be expected to contribute less to productivity; however, when they are pooled with the reporting units that continuously perform positive R&D, then most of the variation in R&D flow in the within-reporting unit dimension is sourced from the reporting units which report positive R&D intermittently (Columns (FE7a), (FE8a), (FE7b), (FE8b)). These concerns suggest that a specification which allows the coefficient on the R&D variable(s) to vary between reporting units which continuously report R&D and those which report R&D intermittently is more desirable.

Based on the distinction between continuous R&D performers and others (including starters, exiters and stop-and-go R&D performers), I define two groups of reporting units which have ever performed R&D in the sample period: first, reporting units which continuously report positive R&D (henceforth labeled as 'regular R&D' in the tables), and second, reporting units which intermittently report positive R&D (labeled 'irregular R&D') to explore the possibly varying degrees of these groups' contributions to productivity.

The different results found for the estimated R&D elasticities when the group level R&D measure and the reporting unit level R&D are used suggest a more general specification which compares the relative importance of the two in one regression. Table 14 presents the results from regressions with the total group level R&D amount interacted with the dummy variables which indicate whether the reporting unit itself does any R&D, and R&D done in the 'rest of the group' (net of R&D done by the reporting unit itself) interacted with the three dummy variables that capture: (i) regular R&D performers, (ii) irregular R&D performers, and (iii) production-only reporting units (No-R&D dummy).

Table 14 suggests that R&D done elsewhere in the group is important for the reporting units which do not perform R&D, and indeed more important for these production-only facilities than it is for the reporting units which do perform R&D. For the R&D units, the main productivity effect comes from the R&D done by the same reporting unit (in most cases, this is the R&D done on-site).

The difference between the left hand and the right hand panels of Table 14 is the way in which the sector dummy variables and time effects are included in the model. The specification used in the left hand panel includes dummy variables for each year and interaction terms for each sector-year pair. The right hand panel presents estimates from a model that includes sector dummies and year dummies separately. The results reported in these two panels of Table 14 are similar enough to support the use of either specification. In the tables that follow Table 14, I include sector and year dummy variables additively in the regressions[24].

[24]Results from the same regressions with sector-year interactions instead of sector dummies have

Table 14: Sub-sample B, relative importance of R&D done by the reporting unit and elsewhere in the same group

	Include year and sector-year interactions				Include year and sector dummies			
	OLS17a	FE17a	OLS18a	FE18a	OLS17b	FE17b	OLS18b	FE18b
L * R&D dum.	0.220***	0.152***	0.277***	0.188***	0.228***	0.168***	0.283***	0.198***
	(0.019)	(0.045)	(0.027)	(0.070)	(0.019)	(0.055)	(0.027)	(0.076)
L * No-R&D dum.	0.280***	0.179***	0.370***	0.413***	0.281***	0.178***	0.371***	0.404***
	(0.005)	(0.016)	(0.004)	(0.019)	(0.005)	(0.017)	(0.004)	(0.021)
M * R&D dum.	0.642***	0.475***	0.585***	0.465***	0.641***	0.479***	0.584***	0.465***
	(0.023)	(0.057)	(0.023)	(0.059)	(0.023)	(0.058)	(0.023)	(0.058)
M * No-R&D dum.	0.614***	0.543***	0.536***	0.447***	0.618***	0.544***	0.538***	0.450***
	(0.007)	(0.019)	(0.006)	(0.017)	(0.007)	(0.019)	(0.007)	(0.017)
K * R&D dum.	0.114***	0.150***	0.110***	0.124***	0.107***	0.117***	0.105***	0.102**
	(0.018)	(0.043)	(0.020)	(0.042)	(0.018)	(0.042)	(0.020)	(0.041)
K * No-R&D dum.	0.099***	0.046***	0.080***	0.023	0.095***	0.048***	0.077***	0.017
	(0.007)	(0.017)	(0.006)	(0.015)	(0.007)	(0.018)	(0.006)	(0.016)
Rep. unit R *	0.025***	0.008	0.021***	0.008	0.024***	0.007	0.021***	0.008
irregular R&D dum.	(0.006)	(0.009)	(0.006)	(0.009)	(0.007)	(0.009)	(0.006)	(0.009)
Rep. unit R *	0.022***	0.027	0.022***	0.028	0.022***	0.019	0.022***	0.022
regular R&D dum.	(0.004)	(0.072)	(0.004)	(0.071)	(0.004)	(0.069)	(0.004)	(0.069)
Rest of group R&D *	0.003	-0.001	0.004	-0.002	0.004	-0.003	0.005	-0.003
irregular R&D dum.	(0.003)	(0.007)	(0.003)	(0.007)	(0.004)	(0.008)	(0.003)	(0.008)
Rest of group R&D *	0.009	0.005	0.006	0.004	0.010*	0.004	0.007	0.003
regular R&D dum.	(0.006)	(0.008)	(0.006)	(0.007)	(0.006)	(0.009)	(0.006)	(0.009)
Rest of group R&D *	0.008***	0.000	0.006***	0.000	0.008***	0.000	0.006***	0.000
non-R&D dum.	(0.001)	(0.002)	(0.001)	(0.002)	(0.001)	(0.002)	(0.001)	(0.002)
R&D dummy	-0.024	.	0.460*	.	-0.008	.	0.465*	.
	(0.087)	.	(0.259)	.	(0.087)	.	(0.261)	.
W * R&D dum.			0.187**	0.034			0.191**	0.037
			(0.086)	(0.092)			(0.086)	(0.096)
W * No-R&D dum.			0.370***	0.371***			0.371***	0.363***
			(0.009)	(0.020)			(0.009)	(0.021)
Year effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Sector-year eff.	Yes	Yes	Yes	Yes	No	No	No	No
R_squared	0.978	0.688	0.984	0.753	0.977	0.663	0.983	0.729
No of total obs	25,970	25,970	25,970	25,970	25,970	25,970	25,970	25,970
No of R&D RU	1,464	1,464	1,464	1,464	1,464	1,464	1,464	1,464
p-values for the tests of equal:								
β_R^{RU} (irreg.=reg. R&D)	0.666	0.792	0.883	0.780	0.766	0.864	0.881	0.837
β_R^{ROG} (irreg.=reg. R&D)	0.422	0.555	0.763	0.554	0.405	0.574	0.738	0.642
β_R^{ROG} (irreg.=reg.=no-R&D)	0.430	0.822	0.800	0.816	0.524	0.850	0.891	0.898
β_L (positive R&D=no-R&D)	0.002	0.572	0.001	0.002	0.005	0.865	0.001	0.009
β_M (positive R&D=no-R&D)	0.240	0.255	0.036	0.759	0.311	0.287	0.051	0.801
β_K (positive R&D=no-R&D)	0.407	0.024	0.133	0.023	0.506	0.116	0.164	0.050

Same footnotes as for Table 12 apply. 'RU' stands for reporting unit, 'ROG' stands for rest of group.

Headcount labor (L), materials (M) and average wage (W) variables are corrected for double counting. Physical capital (K) is not.

Table 14 presents the results based on the preferred specification of this paper, with separate coefficients for each input elasticity depending on R&D and no-R&D status of the reporting unit, and a further differentiation between regular and irregular R&D among the reporting units which have ever reported positive R&D during the sample period[25].

Without the inclusion of any measure of R&D external to the firm, the estimation of the unrestricted model in Table 14 emphasizes the importance of the reporting unit's own R&D on its own productivity for both regular and irregular R&D performers and also does not find any significant differences between these two groups (p-value above 0.75 for Columns (OLS18a-b) and (FE18a-b)). The elasticity of output with respect to the reporting unit's own R&D is estimated to be 2.1-2.2 percent and significant at the 1 percent level in OLS regressions (Columns (OLS18a) and (OLS18b)). The inclusion of reporting unit fixed effects increases the variance of this coefficient estimate for the reporting units which continuously report positive R&D, but the magnitude of the estimated coefficient increases to around 2.8 percent (Columns (FE18a) and (FE18b)). The elasticity of output with respect to the reporting unit's own R&D reduces to 0.8 percent for the irregular performers of R&D, as the zeros are the main source of variation in the time dimension for this group of reporting units and render the within groups estimates close to zero and insignificant. The importance of R&D done in other reporting units belonging to the same group is supported by the positive and significant coefficient on 'rest of group R&D' for the production-only reporting units, which has a magnitude of 0.6 percent in OLS regressions.

5.4 Introducing measures of R&D external to the firm

The next step is to consider some measures of R&D external to the firm, which were introduced in Section 4. I begin by introducing a basic measure for every reporting unit i that is constructed as a weighted sum of all R&D reported by the reporting units that do not belong to unit i's enterprise group, with the weights determined as the share of employment in i in each of the 33 product groups based on the SIC sectors reported in local unit-level information in IDBR. The share of employment in different product groups for each reporting unit may be based on either the distribution of employment within the enterprise group or the reporting unit. In each of the tables that follow, the left hand and the right hand panels differentiate between enterprise group-level weights and reporting unit-level weights.

no effect on the discussion and the conclusions. These tables are available upon request.

[25]Based on the significance of these input coefficients and the p-values reported at the bottom of the table for hypothesis tests on equal coefficients as indicated, it is possible to impose some restrictions on the model presented in Table 14. I prefer to report the results based on this unrestricted model, noting that imposing the restrictions of equal reporting unit level R&D elasticities for irregular, regular and non-performers of R&D, or equal rest of group R&D elasticities for irregular, regular and non-performers of R&D does not change the sign, significance and magnitude of the remaining coefficients.

Table 15: Sub-sample B, introduction of aggregate R&D as measure of external R&D

Aggregate R&D:	wgt. by emp. shares at group level				wgt. by emp. shares at rep. unit level			
	OLS19a	FE19a	OLS20a	FE20a	OLS19b	FE19b	OLS20b	FE20b
L*R&D dum.	0.228***	0.168***	0.283***	0.198***	0.228***	0.168***	0.283***	0.198***
	(0.019)	(0.054)	(0.027)	(0.076)	(0.019)	(0.055)	(0.027)	(0.076)
L*No-R&D dum.	0.281***	0.177***	0.371***	0.404***	0.281***	0.177***	0.371***	0.404***
	(0.005)	(0.017)	(0.004)	(0.021)	(0.005)	(0.017)	(0.004)	(0.021)
M*R&D dum.	0.641***	0.479***	0.584***	0.465***	0.641***	0.479***	0.584***	0.465***
	(0.023)	(0.058)	(0.023)	(0.058)	(0.023)	(0.058)	(0.023)	(0.058)
M*No-R&D dum.	0.617***	0.543***	0.538***	0.450***	0.618***	0.543***	0.538***	0.450***
	(0.007)	(0.019)	(0.007)	(0.017)	(0.007)	(0.019)	(0.007)	(0.017)
K*R&D dum.	0.107***	0.117***	0.105***	0.102**	0.107***	0.118***	0.105***	0.102**
	(0.018)	(0.041)	(0.020)	(0.041)	(0.018)	(0.042)	(0.020)	(0.041)
K*No-R&D dum.	0.095***	0.048***	0.077***	0.017	0.095***	0.048***	0.077***	0.017
	(0.007)	(0.018)	(0.006)	(0.016)	(0.007)	(0.018)	(0.006)	(0.016)
Rep. unit R *	0.024***	0.007	0.021***	0.008	0.024***	0.007	0.021***	0.008
irregular R&D dum.	(0.007)	(0.009)	(0.006)	(0.009)	(0.007)	(0.009)	(0.006)	(0.009)
Rep. unit R *	0.022***	0.02	0.022***	0.022	0.022***	0.019	0.022***	0.022
regular R&D dum.	(0.004)	(0.070)	(0.004)	(0.069)	(0.004)	(0.069)	(0.004)	(0.069)
Rest of group R&D *	0.004	-0.003	0.005	-0.003	0.004	-0.003	0.005	-0.003
irregular R&D dum.	(0.003)	(0.008)	(0.003)	(0.008)	(0.004)	(0.008)	(0.003)	(0.008)
Rest of group R&D *	0.010*	0.004	0.007	0.003	0.010*	0.004	0.007	0.003
regular R&D dum.	(0.006)	(0.009)	(0.006)	(0.009)	(0.006)	(0.009)	(0.006)	(0.009)
Rest of group R&D *	0.008***	0.000	0.006***	0.000	0.008***	0.000	0.006***	0.000
non-R&D dum.	(0.002)	(0.002)	(0.001)	(0.002)	(0.001)	(0.002)	(0.001)	(0.002)
R&D dummy	-0.01	.	0.463*	.	-0.007	.	0.465*	.
	(0.087)	.	(0.261)	.	(0.087)	.	(0.261)	.
External R&D	0.005*	0.004	0.003	0.000	0.002	0.005	0.001	-0.001
	(0.003)	(0.005)	(0.002)	(0.004)	(0.003)	(0.004)	(0.003)	(0.004)
W*R&D dum.			0.191**	0.037			0.191**	0.037
			(0.086)	(0.096)			(0.086)	(0.096)
W*No-R&D dum.			0.371***	0.363***			0.371***	0.363***
			(0.009)	(0.021)			(0.009)	(0.021)
Year effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Sector-year eff.	No	No	No	No	No	No	No	No
R_squared	0.977	0.664	0.983	0.729	0.977	0.664	0.983	0.729
No of total obs	25,970	25,970	25,970	25,970	25,970	25,970	25,970	25,970
No of R&D RU	1,464	1,464	1,464	1,464	1,464	1,464	1,464	1,464
p-values for the tests of equal:								
β_R^{RU} (irreg.=reg. R&D)	0.759	0.857	0.885	0.836	0.763	0.859	0.883	0.837
β_R^{ROG} (irreg.=reg. R&D)	0.386	0.566	0.724	0.642	0.402	0.574	0.735	0.642
β_R^{ROG} (irreg.=reg.=no-R&D)	0.518	0.846	0.889	0.897	0.520	0.850	0.889	0.898
β_L (positive R&D=no-R&D)	0.006	0.871	0.001	0.009	0.005	0.874	0.001	0.009
β_M (positive R&D=no-R&D)	0.310	0.290	0.051	0.800	0.310	0.284	0.051	0.800
β_K (positive R&D=no-R&D)	0.502	0.116	0.163	0.050	0.510	0.113	0.165	0.050

Same footnotes as for Table 14 apply.

Using this crude measure of external R&D that is along the lines of Bernstein and Nadiri (1989), there does not appear to be a significant productivity effect of R&D external to the firm. Allowing for a more flexible specification with the external R&D measure varying between R&D and no-R&D reporting units does not find significant effects in either, with p-values for the test of equal coefficients of 0.843 when the measure of external R&D uses group level weights and 0.743 when this measure uses reporting unit level weights (Columns (OLS20a) and (OLS20b)). The inclusion of the external R&D measure does not affect the estimates of elasticity of output with respect to the reporting unit's own R&D and R&D done elsewhere in the group.

Given the desirable properties of spillover measures established in BSV, the Jaffe (1986) distance measure may be preferable to the basic sector level R&D aggregates which do not reflect the interactions between firms. For this large sample which includes groups without any R&D operation, the productivity effects of R&D external to the firms can only be quantified using the distribution of employment across different sectors. Sectors of R&D activity which allows for the construction of the Jaffe (1986) measure of external R&D is only available for the long form recipients, and this dimension will be explored on Sub-sample C in Section 5.5. Table 16 presents the results from a specification which includes a variable that captures R&D done by product market rivals to explore the effect of any interaction in product space on productivity.

In Table 16, in Column (OLS20b) the OLS coefficient on the measure of external R&D is positive and significant when the 'production profile of the reporting unit' (in the right hand panel of the table) is used to construct this metric, with a magnitude of 0.2 percent. The inclusion of reporting unit fixed effects in Column (FE20b) increases the variance of the estimate and the coefficient is no longer significant, but it is still positive. If group level production profiles are used to measure external R&D, no effect of external R&D can be observed on productivity. This is in line with the importance of the reporting unit level measure in the elasticity of output with respect to the reporting unit's own R&D. Elasticity of output with respect to the reporting unit's own R&D and other input elasticities are estimated with similar magnitudes, signs and significance as in Table 14.

5.5 Measures of external R&D on the long form sample

Section 4 discussed the advantages of BERD long form information, which provides breakdowns of R&D activity within firms or reporting units for constructing the technology spillover measure developed by Jaffe (1986) and discussed in BSV. Using Sub-sample C and the BERD long form information, it is possible to estimate the specification derived by the theoretical model in BSV and apply to the BERD-ARD data. In this section, I first present the results from the preferred specification used in the regressions in Table 14 applied to Sub-sample C to demonstrate the differences between Sub-sample B and Sub-sample C. I then introduce the crude measures of external R&D based

Table 16: Sub-sample B, introduction of the Jaffe measure for external R&D

Jaffe product market:	wgt. by emp. shares at group level				wgt. by emp. shares at rep. unit level			
	OLS19a	FE19a	OLS20a	FE20a	OLS19b	FE19b	OLS20b	FE20b
L*R&D dum.	0.228***	0.168***	0.283***	0.198***	0.226***	0.166***	0.282***	0.197***
	(0.019)	(0.054)	(0.027)	(0.076)	(0.019)	(0.054)	(0.027)	(0.076)
L*No-R&D dum.	0.281***	0.178***	0.371***	0.404***	0.279***	0.178***	0.370***	0.404***
	(0.005)	(0.017)	(0.004)	(0.021)	(0.005)	(0.017)	(0.004)	(0.021)
M*R&D dum.	0.641***	0.480***	0.584***	0.466***	0.637***	0.479***	0.581***	0.465***
	(0.023)	(0.057)	(0.023)	(0.058)	(0.023)	(0.058)	(0.023)	(0.058)
M*No-R&D dum.	0.618***	0.543***	0.538***	0.450***	0.616***	0.544***	0.537***	0.450***
	(0.007)	(0.019)	(0.007)	(0.017)	(0.007)	(0.019)	(0.007)	(0.017)
K*R&D dum.	0.107***	0.116***	0.105***	0.101**	0.109***	0.118***	0.106***	0.102**
	(0.018)	(0.041)	(0.020)	(0.041)	(0.018)	(0.042)	(0.020)	(0.041)
K*No-R&D dum.	0.095***	0.047***	0.077***	0.017	0.096***	0.046***	0.078***	0.016
	(0.007)	(0.018)	(0.006)	(0.016)	(0.007)	(0.018)	(0.006)	(0.016)
Rep. unit R *	0.024***	0.007	0.021***	0.008	0.024***	0.007	0.021***	0.007
irregular R&D dum.	(0.007)	(0.009)	(0.006)	(0.009)	(0.007)	(0.009)	(0.006)	(0.009)
Rep. unit R *	0.022***	0.020	0.022***	0.022	0.022***	0.019	0.022***	0.022
regular R&D dum.	(0.004)	(0.069)	(0.004)	(0.069)	(0.004)	(0.070)	(0.004)	(0.069)
Rest of group R&D *	0.004	-0.003	0.005	-0.003	0.005	-0.003	0.005*	-0.003
irregular R&D dum.	(0.004)	(0.008)	(0.003)	(0.008)	(0.004)	(0.008)	(0.003)	(0.008)
Rest of group R&D *	0.010*	0.004	0.007	0.003	0.009*	0.004	0.007	0.003
regular R&D dum.	(0.006)	(0.009)	(0.006)	(0.009)	(0.006)	(0.009)	(0.006)	(0.009)
Rest of group R&D *	0.008***	0.000	0.007***	-0.001	0.008***	0.000	0.006***	0.000
non-R&D dum.	(0.001)	(0.002)	(0.001)	(0.002)	(0.001)	(0.002)	(0.001)	(0.002)
R&D dummy	-0.008	.	0.464*	.	-0.005	.	0.464*	.
	(0.087)	.	(0.261)	.	(0.088)	.	(0.261)	.
External R&D	-0.001	0.002	0.000	0.002	0.003***	0.013*	0.002***	0.007
	(0.002)	(0.002)	(0.001)	(0.002)	(0.001)	(0.008)	(0.001)	(0.008)
W*R&D dum.			0.191**	0.037			0.191**	0.037
			(0.086)	(0.096)			(0.086)	(0.096)
W*No-R&D dum.			0.371***	0.363***			0.370***	0.363***
			-0.009	-0.021			(0.009)	(0.021)
Year effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Sector-year eff.	No	No	No	No	No	No	No	No
R_squared	0.977	0.664	0.983	0.730	0.977	0.664	0.983	0.73
No of total obs	25,970	25,970	25,970	25,970	25,970	25,970	25,970	25,970
No of R&D RU	1,464	1,464	1,464	1,464	1,464	1,464	1,464	1,464
p-values for the tests of equal:								
β_R^{RU} (irreg.=reg. R&D)	0.761	0.859	0.882	0.834	0.856	0.860	0.823	0.835
β_R^{ROG} (irreg.=reg. R&D)	0.405	0.581	0.737	0.647	0.513	0.569	0.813	0.640
β_R^{ROG} (irreg.=reg.=no-R&D)	0.523	0.856	0.891	0.900	0.683	0.847	0.948	0.896
β_L (positive R&D=no-R&D)	0.005	0.861	0.001	0.009	0.006	0.838	0.001	0.009
β_M (positive R&D=no-R&D)	0.315	0.292	0.051	0.794	0.366	0.281	0.059	0.806
β_K (positive R&D=no-R&D)	0.498	0.120	0.163	0.051	0.471	0.105	0.158	0.047

Same footnotes as for Table 14 apply.

on aggregate sector BERD, followed by the introduction of Jaffe (1986) product market and technology spillover measures.

Table 17 shows that the estimated elasticities of output with respect to the traditional inputs headcount labor, capital and materials are also different from those estimated using Sub-sample B. Focusing on the third column labeled Column (OLS22), and comparing it with the corresponding Column (OLS18b) in Table 14 for the reporting units that have had positive R&D in the sample period, we observe that the coefficient on labor went down from 28 percent in Sub-sample B to 21 percent in Sub-sample C. For the same group, the coefficient on materials decreased from 58 to 53 percent and the coefficient on capital increased by 2 percentage points to 13 percent. The change in the OLS estimates for the reporting units that continuously reported positive R&D during the sample period is large in magnitude, from 2.2 percent to 3.3 percent. The p-value for the formal test of the hypothesis that the coefficients on regular and irregular reporters of positive R&D remains nevertheless large, at 0.391 and we cannot reject the null hypothesis that the elasticity of output with respect to the reporting unit's own R&D is the same for these two groups. Another difference between Tables 17 and 14 is that the R&D performed by the rest of the enterprise group is no longer significant, although the magnitude of the estimated coefficient is still in the same ballpark, at 0.6 percent. Since the sample size is much smaller in Sub-sample C, we may prefer a more parsimonious specification, imposing the restriction that the elasticities of output with respect to the reporting unit's own R&D is the same for irregular and regular spenders in R&D. Additionally, I impose equal coefficients on R&D performed by the rest of the group for irregular, regular and non-performers of R&D, which is not rejected in the results presented in Table 17. The choice of which restrictions (out of the hypotheses that are not rejected in Table 17) are imposed does not make a substantive difference on the results that are presented in the remaining tables in this section.

Tables 18 and 19 present estimates from specifications that add measures of external R&D to the regressions presented in Table 17. As before, all measures of R&D external to the firm are weighted by group level and reporting unit level distribution of activity separately and presented in the left hand and the right hand panels of the two tables. All inputs are corrected for double counting.

The specification estimated in Table 18 uses the aggregate sector-level R&D as the measure of external R&D. The aggregate BERD as an input to the production process of each reporting unit i is calculated as a weighted sum of all external R&D, with the weights determined as the shares of employment in each of the 33 product fields provided in the local unit information of IDBR. In Table 18, the estimated elasticity of output with respect to external R&D is 2 percent and significant at the 5 percent level in OLS regressions (Column (OLS24a)) with the external R&D weights determined at the enterprise group level, and insignificant when reporting unit fixed effects are included (Column (FE24a)) and when the external R&D measure uses weights as employment shares at the reporting unit level (Columns (OLS23b)-(FE24b)). OLS estimates of own R&D elasticity with R&D measured at the reporting unit level are positive and significant at 1 percent level with a magnitude of 2.7 percent, and when R&D is measured as that performed by the rest of the group is positive and significant at the 10 percent level with a magnitude of 0.5 percent. Elasticities of output with respect to labor (headcount and quality), materials and capital are estimated with similar signs, magnitudes and significance as in the case without the inclusion of external R&D measures (Table 17).

Finally, Table 19 presents estimates which are based on the model proposed by BSV, with separate measures of external R&D included for the effects of R&D performed by neighboring firms in product market and technology space. Reporting units which themselves have ever performed R&D (in the sample period) and which have not are accounted for separately and labeled accordingly in the table as the effects appear to be different for these two types of observations for some of the measures of external R&D. The variable labeled 'External R&D, TECH.' in the table stands for the version of the Jaffe (1986) measure of external R&D that quantifies the extent of interactions in technology space, which the theoretical model in BSV predicts to be positive. Similarly, the variable 'External R&D, PRD.MKT.' represents the total R&D performed by neighboring firms in the product market space, for which BSV is agnostic about the productivity effects.

In the left hand panel of Table 19, where the Jaffe (1986) weights are determined by the distribution of activity within the enterprise group, the OLS estimate for the productivity of external R&D performed by neighboring firms in the technology space appears to be positive and marginally significant, with a magnitude of 2 percent (Columns (OLS26a)). The introduction of reporting unit level fixed effects reduces this estimate to being insignificant, whereas R&D by product market competitors appear to be marginally significant only after reporting unit fixed effects are introduced. For reporting units that do not themselves perform R&D, the coefficients on both measures of external R&D are insignificant. The remaining input elasticities are not affected substantially by the inclusion of these measures in the regressions.

The right hand panel of Table 19 uses the versions of the Jaffe (1986) weights at the reporting unit level. Given that almost all the reporting units in this sample only perform R&D in a single product field, for most of the reporting units, the measure of external R&D by neighboring reporting units in technology space reduces to the total R&D performed in reporting unit i's own R&D product field, net of R&D carried out in that product field by the enterprise group that owns reporting unit i. The results regarding the measure of external R&D by neighboring reporting units in technology space (that are outside the reporting unit's own enterprise group) appear to take on a negative and significant coefficient, which in turn causes the coefficient on own R&D to increase to 6.5 percent. This result is puzzling, and a possible explanation relates to the construction of the reporting unit-level technology spillover measure, where the reporting unit's own productivity depends on its share of the total R&D done in a given product field. The larger the reporting unit's own share in the aggregate sector-level R&D, the smaller is the productivity effect of external R&D. Using reporting unit level

R&D totals in each reporting unit's own product field (without netting out the group's own R&D in that field) instead of the Jaffe (1986) measure of external R&D by neighbors in technology space reverses the sign of this coefficient.

BSV uses a large number of technology classes based on patent data to capture the impact of R&D that is external to the firms on their own productivity and finds positive effects of R&D done by neighboring firms in technology space. Additionally, BSV considers the R&D performed in the whole group which is a closer measure to the one used in the left hand panel of Table 19. Future work may consider merging patent data to the BERD-ARD data set to explore weighting external R&D by more detailed technology profiles for patenting firms to construct the Jaffe (1986) measure.

Table 17: Sub-sample C, results from the preferred specification with double counting correction

	OLS21	FE21	OLS22	FE22
L*R&D dum.	0.173***	0.189***	0.206***	0.186***
	(0.029)	(0.050)	(0.034)	(0.063)
L*No-R&D dum.	0.230***	0.174**	0.283***	0.205***
	(0.020)	(0.072)	(0.028)	(0.079)
M*R&D dum.	0.553***	0.417***	0.527***	0.417***
	(0.029)	(0.065)	(0.030)	(0.064)
M*No-R&D dum.	0.684***	0.672***	0.636***	0.613***
	(0.028)	(0.072)	(0.028)	(0.075)
K*R&D dum.	0.130***	0.040	0.125***	0.042
	(0.033)	(0.076)	(0.034)	(0.075)
K*No-R&D dum.	0.075***	-0.006	0.066***	-0.007
	(0.024)	(0.054)	(0.023)	(0.054)
Rep. unit R *	0.026***	0.008	0.025***	0.009
irregular R&D dum.	(0.008)	(0.008)	(0.007)	(0.009)
Rep. unit R *	0.034***	0.031	0.033***	0.031
regular R&D dum.	(0.011)	(0.047)	(0.010)	(0.047)
Rest of group R&D *	0.011	(0.005)	0.010	(0.004)
irregular R&D dum.	(0.009)	(0.009)	(0.008)	(0.009)
Rest of group R&D *	0.007*	-0.003	0.005	-0.003
regular R&D dum.	(0.004)	(0.006)	(0.004)	(0.006)
Rest of group R&D *	0.011*	-0.013	0.007	-0.010
non-R&D dum.	(0.006)	(0.014)	(0.005)	(0.013)
R&D dummy	1.228***	.	1.392***	.
	(0.295)	.	(0.375)	.
W*R&D dum.			0.102	0.000
			(0.069)	(0.073)
W*No-R&D dum.			0.190***	0.110*
			(0.063)	(0.065)
Year effects	Yes	Yes	Yes	Yes
Sector-year eff.	No	No	No	No
R_squared	0.955	0.668	0.959	0.681
No of total obs	1,765	1,765	1,765	1,765
No of R&D RU	677	677	677	677
p-values for the tests of equal:				
β_R^{RU} (irreg.=reg. R&D)	0.343	0.626	0.391	0.635
β_R^{ROG} (irreg.=reg. R&D)	0.629	0.893	0.570	0.898
β_R^{ROG} (irreg.=reg.=no-R&D)	0.774	0.813	0.821	0.895
β_L (positive R&D=no-R&D)	0.089	0.867	0.072	0.856
β_M (positive R&D=no-R&D)	0.001	0.008	0.007	0.044
β_K (positive R&D=no-R&D)	0.125	0.606	0.109	0.579

Same footnotes as for Table 14 apply.

Table 18: Sub-sample C, inclusion of aggregate measures of external R&D (preferred specification with double counting correction)

Aggregate R&D:	wgt. by emp. shares at group level				wgt. by emp. shares at rep. unit level			
	OLS23a	FE23a	OLS24a	FE24a	OLS23b	FE23b	OLS24b	FE24b
L*R&D dum.	0.175***	0.190***	0.209***	0.188***	0.173***	0.190***	0.206***	0.187***
	(0.029)	(0.050)	(0.035)	(0.062)	(0.029)	(0.050)	(0.035)	(0.063)
L*No-R&D dum.	0.231***	0.172**	0.283***	0.203**	0.232***	0.171**	0.285***	0.202**
	(0.020)	(0.072)	(0.027)	(0.079)	(0.020)	(0.071)	(0.028)	(0.079)
M*R&D dum.	0.552***	0.417***	0.526***	0.417***	0.552***	0.418***	0.527***	0.418***
	(0.029)	(0.066)	(0.030)	(0.064)	(0.029)	(0.066)	(0.030)	(0.065)
M*No-R&D dum.	0.685***	0.673***	0.638***	0.613***	0.683***	0.673***	0.635***	0.613***
	(0.027)	(0.072)	(0.027)	(0.075)	(0.028)	(0.073)	(0.028)	(0.075)
K*R&D dum.	0.133***	0.038	0.128***	0.041	0.134***	0.04	0.129***	0.042
	(0.033)	(0.074)	(0.034)	(0.073)	(0.033)	(0.075)	(0.034)	(0.074)
K*No-R&D dum.	0.074***	-0.005	0.065***	-0.007	0.076***	-0.004	0.067***	-0.005
	(0.023)	(0.054)	(0.023)	(0.054)	(0.024)	(0.054)	(0.023)	(0.055)
Rep. unit R	0.029***	0.009	0.027***	0.01	0.029***	0.009	0.027***	0.01
	(0.005)	(0.008)	(0.005)	(0.008)	(0.005)	(0.008)	(0.005)	(0.008)
Rest of group R&D	0.007**	-0.003	0.005*	-0.003	0.007**	-0.004	0.005*	-0.003
	(0.003)	(0.005)	(0.003)	(0.005)	(0.003)	(0.005)	(0.003)	(0.005)
R&D dummy	1.198***	.	1.385***	.	1.207***	.	1.396***	.
	(0.281)	.	(0.379)	.	(0.280)	.	(0.378)	.
External R&D (E)	0.021**	0.008	0.020**	0.009	-0.006	-0.003	-0.004	-0.003
	(0.011)	(0.019)	(0.009)	(0.019)	(0.005)	(0.004)	(0.004)	(0.004)
W*R&D dum.			0.103	-0.001			0.102	-0.001
			(0.069)	(0.074)			(0.069)	(0.074)
W*No-R&D dum.			0.190***	0.111*			0.191***	0.111*
			(0.062)	(0.065)			(0.063)	(0.065)
Year effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Sector-year eff.	No	No	No	No	No	No	No	No
R_squared	0.955	0.668	0.959	0.680	0.955	0.668	0.959	0.68
No of total obs	1,765	1,765	1,765	1,765	1,765	1,765	1,765	1,765
No of R&D RU	677	677	677	677	677	677	677	677
p-values for the tests of equal:								
β_E (positive R&D=no-R&D)	0.869	0.495	0.943	0.426	0.321	0.905	0.333	0.791
β_L (positive R&D=no-R&D)	0.102	0.826	0.080	0.877	0.083	0.826	0.067	0.878
β_M (positive R&D=no-R&D)	0.001	0.008	0.005	0.045	0.001	0.008	0.007	0.047
β_K (positive R&D=no-R&D)	0.096	0.618	0.089	0.584	0.106	0.619	0.096	0.586

Same footnotes as for Table 14 apply.

Table 19: Sub-sample C, inclusion of Jaffe (1986) measures of external R&D (preferred specification with double counting correction)

Jaffe (1986) weights:	wgt. by activity at group level				wgt. by activity at rep. unit level			
	OLS25a	FE25a	OLS26a	FE26a	OLS25b	FE25b	OLS26b	FE26b
L*R&D dum.	0.176***	0.191***	0.208***	0.188***	0.169***	0.188***	0.200***	0.186***
	(0.030)	(0.050)	(0.034)	(0.063)	(0.028)	(0.051)	(0.033)	(0.064)
L*No-R&D dum.	0.231***	0.168**	0.284***	0.199**	0.233***	0.172**	0.286***	0.203**
	(0.020)	(0.072)	(0.028)	(0.079)	(0.020)	(0.072)	(0.028)	(0.079)
M*R&D dum.	0.551***	0.421***	0.526***	0.421***	0.554***	0.416***	0.531***	0.416***
	(0.029)	(0.066)	(0.031)	(0.065)	(0.029)	(0.065)	(0.030)	(0.063)
M*No-R&D dum.	0.685***	0.677***	0.637***	0.616***	0.683***	0.673***	0.635***	0.613***
	(0.028)	(0.073)	(0.028)	(0.076)	(0.028)	(0.073)	(0.028)	(0.076)
K*R&D dum.	0.134***	0.033	0.129***	0.036	0.122***	0.035	0.118***	0.038
	(0.033)	(0.073)	(0.034)	(0.073)	(0.033)	(0.075)	(0.033)	(0.075)
K*No-R&D dum.	0.075***	-0.005	0.067***	-0.007	0.073***	-0.005	0.064***	-0.007
	(0.024)	(0.054)	(0.023)	(0.055)	(0.024)	(0.053)	(0.023)	(0.053)
Rep. unit R	0.028***	0.008	0.026***	0.009	0.070***	0.037	0.065***	0.037
	(0.005)	(0.008)	(0.005)	(0.008)	(0.016)	(0.033)	(0.016)	(0.033)
Rest of group R&D	0.006*	-0.004	0.004	-0.004	0.005*	-0.004	0.004	-0.004
	(0.003)	(0.005)	(0.003)	(0.005)	(0.003)	(0.005)	(0.003)	(0.005)
R&D dummy	0.934***	.	1.122***	.	1.303***	.	1.508***	.
	(0.358)	.	(0.388)	.	(0.305)	.	(0.389)	.
External R&D (E), TECH. *	0.022*	-0.002	0.020*	-0.002	-0.031***	-0.020	-0.029**	-0.019
positive R&D dum.	(0.012)	(0.015)	(0.012)	(0.015)	(0.011)	(0.021)	(0.011)	(0.021)
External R&D (E), TECH. *	0.003	0.005	0.003	0.006	.	.	.	.
non-R&D dum.	(0.005)	(0.006)	(0.005)	(0.005)	.	.	.	.
External R&D (E), PRD.MKT. *	0.01	0.020*	0.006	0.020*	0.006	0.000	0.006	0.000
positive R&D dum.	(0.012)	(0.011)	(0.012)	(0.011)	(0.007)	(0.004)	(0.007)	(0.004)
External R&D (E), PRD.MKT. *	0.009	0.000	0.003	0.004	0.001	-0.001	0.002	-0.001
non-R&D dum.	(0.008)	(0.008)	(0.008)	(0.008)	(0.003)	(0.003)	(0.003)	(0.003)
W*R&D dum.			0.100	0.000			0.093	-0.001
			(0.068)	(0.072)			(0.066)	(0.073)
W*No-R&D dum.			0.190***	0.112*			0.192***	0.111*
			(0.063)	(0.065)			(0.063)	(0.065)
Year effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Sector-year eff.	No	No	No	No	No	No	No	No
R_squared	0.955	0.669	0.959	0.682	0.956	0.669	0.96	0.682
No of total obs	1,765	1,765	1,765	1,765	1,765	1,765	1,765	1,765
No of R&D RU	677	677	677	677	677	677	677	677
p-values for the tests of equal:								
$\beta_E^{TECH.}$ (pos.R&D=no-R&D)	0.130	0.646	0.168	0.586	0.007	0.356	0.011	0.368
$\beta_E^{PRD.M.}$ (pos.R&D=no-R&D)	0.954	0.147	0.840	0.223	0.576	0.872	0.546	0.846
β_L (positive R&D=no-R&D)	0.114	0.786	0.078	0.917	0.054	0.848	0.041	0.861
β_M (positive R&D=no-R&D)	0.001	0.008	0.007	0.049	0.001	0.007	0.008	0.043
β_K (positive R&D=no-R&D)	0.107	0.661	0.097	0.620	0.159	0.648	0.133	0.615

Same footnotes as for Table 14 apply.

Jaffe (1986) TECH. measure applies weights according to distribution of activity across R&D product fields.

Jaffe (1986) PRD.MKT. measure applies weights according to distribution of employment across product fields obtained from SIC sectors in IDBR.

6 Conclusion

This paper has presented basic static production function estimates using micro level data on UK manufacturing reporting units' production and R&D information from ARD and BERD data sets over a period of 11 years. There are three main contributions of the paper. First, the detailed information in the BERD data set on the breakdown of current spending on R&D enabled the estimation of the production function after having corrected the measurement of traditional inputs for the double-counting of R&D labor (headcount and quality) and materials. This has been shown to result in higher magnitude and significance of the own R&D elasticity estimates, and smaller magnitudes of the coefficients on headcount labor and labor quality (average wage). Additionally, input elasticities have shown a considerable degree of heterogeneity across reporting units which themselves perform R&D and those that are production-only.

Second, I provide evidence that R&D performed by the other members of the enterprise group has productivity effects for the production-only facilities that belong to groups with some R&D activity. Exploring the differences in input elasticities across positive R&D reporting units and production-only facilities support that both the elasticities of output with respect to the traditional inputs and with respect to the enterprise group's own R&D differ across these two types of reporting units. In a comparison between the informativeness of the group's total R&D and the reporting unit's R&D, the latter seems to be more informative for the productivity of the reporting units that themselves carry out R&D activities.

Third, the information from BERD long forms on the fields of R&D activity and the local unit detailed manufacturing product group information on the breakdown of employment to product groups proved to be useful resources to consider state-of-the-art spillover measures recently developed by Bloom et al. (2013) based on the seminal work of Jaffe (1986). The results from the analysis on the measures of external R&D with the Bloom et al. (2013)/Jaffe (1986) weights pointed at a positive and significant effect of R&D performed by neighboring firms in the technology space on the reporting unit's own output when the enterprise group level measures of R&D external to the firm have been used, but future work may address the mixed results from regressions which use reporting unit-level weights for the same measures.

The OLS and FE estimates of gross output production functions with the traditional labor (head-count and quality adjustment), capital and materials inputs yielded elasticity point estimates that are positive and significant and with magnitudes in the ballpark of the relevant cost shares of these factors. An important aspect of this specification was the inclusion of the average wage variable as a proxy for labor quality, which is ignored in many studies. The inclusion of the firms' or reporting units' own R&D input did not change the magnitude or significance of these coefficients substantially, and resulted in modest in magnitude but statistically significant estimates of the elasticity of output with respect to the firms' or reporting unit's own R&D input, at an order of magnitude around 0.6 percent. The double-counting correction for labor and materials allowed the elasticity estimates with respect to the reporting unit's own R&D input to increase up to 3 percent for the positive R&D reporting units, reducing the magnitudes of the estimated coefficients on headcount labor and average wage. In the absence of the average wage variable, the coefficient on the variable for the reporting unit's own R&D seemed to capture the effect of this variable, causing the productivity of R&D to be overestimated. For the production-only facilities, the elasticity of output with respect to the rest of the group's R&D was estimated to be up to 0.6 percent after the double counting correction.

A Data appendix

A.1 Data cleaning

Before any merges with the BERD data, all the ARD observations with missing or zero employment and intermediate inputs, missing capital expenditure information and negative gross output were removed from the data set (first cleaning step in Table 20). The capital stock values were constructed using the perpetual inventory method, from net capital expenditure data and assuming a depreciation rate of 6 percent. The construction of the capital stock required that the same reporting unit be followed over continuous time spells of at least two periods (second cleaning step). If there are gaps between groups of consecutive observations for a reporting unit, then the longest spell of consecutive observations is kept in the data set, while the others are removed. In the third cleaning step, the following observations are dropped: if materials, labor costs or headcount employment is zero or missing; if the observation lies in the 1st and 99th percentile of capital stock (this removes any negatives), and gross output; if cost shares of materials or labor exceed unity, and the bottom 1st percentile observations for these ratios; the bottom percentile of the 'remainder' capital cost share obtained by subtracting the labor and materials cost shares from unity. If the growth rate of labor costs, materials, capital stock or gross output is greater than 3 or less than -3 in any period, the whole reporting unit is dropped. In the fourth cleaning step, observations that have missing 'beginning-of-period (lagged)' capital are dropped and finally, the fifth cleaning step removes any enterprise groups that have any imputed information on R&D. Enterprise groups which have no connection to an R&D performing reporting unit have been kept in the data set.

The number of reporting units in each period for these data cleaning steps can be found in Table 20.

Before any cleaning, ARD-BERD matches in terms of the number of reporting units merged on the reporting unit reference or the enterprise group reference can be observed in Table 21. After the cleaning steps described above, the number of matched observations in the same way drops, and the revised number of observations after cleaning is presented in Table 22.

For the construction of the R&D capital stock, there is a stricter requirement that a match needs to take place between a continuously sampled BERD and a continuously sampled ARD reporting unit. Table 22 allows for gaps in R&D spending, considering that the enterprise group level R&D flow is used instead of the stock variable in the main analysis.

A.2 Variables

A few alternatives are available in the ARD data set for the input and output variables and the choice of variables in the preferred specifications depended on data quality. Some of the variables

Table 20: Number of observations after data cleaning steps for ARD reporting units

	ARD manufacturing	Cleaning Step I	Cleaning Step II	Cleaning Step III	Cleaning Step IV	Cleaning Step V	Cleaning Step VI
1997	12,080	11,873	5,460	4,711			
1998	12,581	12,256	7,473	6,185	4,239	3,348	2,682
1999	12,427	12,093	8,171	6,659	4,325	3,857	3,231
2000	12,250	11,937	7,949	6,433	4,220	3,562	2,943
2001	12,868	12,616	8,058	6,539	4,133	3,631	3,043
2002	11,839	11,611	7,573	6,226	4,298	3,385	2,828
2003	11,576	11,371	7,168	5,870	4,013	3,417	2,930
2004	11,219	11,018	6,702	5,443	3,899	3,254	2,785
2005	10,661	10,177	6,026	4,761	3,361	2,632	2,265
2006	9,619	9,308	5,213	4,022	2,822	2,126	1,766
2007	7,624	7,494	4,270	3,309	2,519	1,868	1,549
2008	6,904	6,637	2,373	1,765	1,594	1,274	1,016
Total	131,648	128,391	76,436	61,923	39,423	32,354	27,038

Table 21: Continuously sampled manufacturing ARD matched with BERD

	All, matched on:		Non-imputed, matched on:		Long form, matched on:	
period	rep.unit	ent. group	rep.unit	ent. group	rep.unit	ent. group
1997	983	1,891	434	1,185	110	488
1998	1,876	2,919	651	1,540	119	563
1999	1,657	2,752	867	1,772	141	554
2000	1,826	2,859	836	1,740	141	536
2001	1,539	2,538	716	1,529	147	549
2002	2,008	2,855	686	1,386	145	471
2003	1,518	2,321	666	1,342	118	411
2004	1,743	2,427	813	1,399	118	388
2005	1,659	2,209	635	1,114	124	338
2006	1,635	2,140	571	960	126	320
2007	1,512	1,972	558	913	114	288
2008	839	1,162	391	629	96	229
Total	18,795	28,045	7,824	15,509	1,499	5,135

available in the ARD which are relevant for the production function estimation context are listed below, and an asterisk (*) indicates the variables which were used in the main gross output production functions, or in the construction of these variables. Variable definitions and some notes are included for information.

go(*): gross output, obtained by adding total turnover with end of period net of beginning of period stocks of finished goods and materials.

gva_mp: gross value added at market prices, obtained by adding total turnover with the total value of all beginning of period value of stocks of goods and materials including work in progress, capital work by own staff, value of insurance claims received less total purchases of goods, materials

Table 22: Number of reporting units in the clean ARD data set after cleaning step IV matched with BERD

	All, matched on:		Non-imputed, matched on:		Long form, matched on:	
period	rep.unit	ent. group	rep.unit	ent. group	rep.unit	ent. group
1998	1,339	1,983	448	1,034	57	331
1999	1,010	1,641	542	1,055	58	274
2000	1,199	1,757	541	1,046	56	252
2001	959	1,537	457	933	78	293
2002	1,357	1,843	444	870	74	263
2003	1,048	1,516	452	872	60	238
2004	1,223	1,649	578	946	54	206
2005	1,136	1,468	407	729	59	181
2006	1,045	1,326	349	571	60	177
2007	997	1,263	346	561	45	140
2008	572	774	252	399	44	121
Total	11,885	16,757	4,816	9,016	645	2,476

and services.

gva_fc: sum of **gva_mp** and subsidies received from the UK government and the European Commission, less total taxes, duties, levies net of excise drawback

idbr_to: turnover, based on IDBR records.

to: total turnover reported in the ABI return.

ncapex(*): net capital expenditure, with a breakdown into plant and machinery (**ncapex_pm**), buildings (**ncapex_b**) and vehicles (**ncapex_v**).

totpurch(*): total purchases of goods, materials and services.

empment(*): total employment, based on IDBR records.

totlabcost(*): total employment costs, including insurance payments.

matfuel: purchases of energy and water products and purchases of goods and materials for own consumption.

matpurch: purchases of goods and materials for own consumption. This variable includes fuels and electricity, but excludes business services.

A.3 Initial values for physical capital

Apportioning an estimate for aggregate capital stock to individual reporting units is one way of obtaining a proxy for initial capital stock values. Volume Index of Capital Services (VICS) is a publicly available sector and asset-level data set which measures the capital input into the production process. It provides information on aggregate gross fixed capital formation (GFCF), net stock of capital goods by asset types (plant and machinery, buildings, vehicles) and the implied deflators obtained by dividing the current price GFCF by the constant price GFCF. Various ONS studies support that VICS is an appropriate source for capital stock data to conduct productivity analyses[26].

Initial capital calculations involve apportioning the net capital stock provided in the aggregate VICS tables to the individual reporting units using each reporting unit's share of materials and services purchases **totpurch** to the total materials and services purchases within their respective two digit SIC sector. Any other variable than materials and services purchases may be selected, based on the distribution of the ratio of this variable to capital across firms within a given sector. The share of firm i's material use in total in its two digit sector category is:

$$m_{0s_i} = \frac{x_{s_i}}{\sum_{i \in A_s} x_{s_i}} \tag{15}$$

where x is the variable that captures the purchases of materials and fuel, and A_s is the set of all observations in sector s.

Since the ARD is a stratified sample of small and medium sized enterprises, the total capital represented by the observations in our sample constitutes only part of the aggregate capital stock. If the total aggregate capital stock is apportioned to the enterprises in the sample without taking unsampled observations into consideration, the initial capital stock values will be over-estimated. Consequently, the aggregate data is scaled to reflect the sample more closely by assuming that the share of the sample's total capital stock to the aggregate capital from VICS in a given sector is proportional to the share of investment in the sample to the aggregate investment by the firms in that sector category in a given period.

The VICS data sets are available in 2005 prices. In order to conform to the remaining variables in the productivity estimation stages, all values have been converted to 1997 prices. The rebasing was carried out using the deflator sheet which was made available along with the VICS data sets.

A.4 Deflators

Output deflators have been extracted from the producer price index (PPI) series by the ONS for sectors at the four digit level. When the index for the relevant four digit sector is not available, the corresponding three digit sector's output price index has been used. When the PPI for neither four, nor three digit sectors are available, then the two digit sector deflators are used. If a mapping between the sector in the data set and the ONS PPI series cannot be found, the overall manufacturing sector PPI for outputs produced in the UK are used.

In the same PPI release as for the output price indices, information on the prices of materials and fuel input is available. A similar procedure to that for the output price deflators has been used to map the reporting units in the ARD data set with their corresponding deflator series.

[26] See, for instance, Appleton and Wallis (2011), Gilhooly (2009)

Labor input deflators have been constructed using the Annual Survey of Hours and Earnings data from the ONS, which is available for the period 1997-2013. Mean and median weekly earnings for each two-digit sector category is available for all years, while mean and median annual earnings are available from 1999 onwards. We therefore use the median weekly earnings averaged over the year as the index for labor input. The earnings information uses SIC 1992 for the period 1997-2001, SIC 2003 for the period 2002-2007, and SIC 2007 for the period 2008-2009. The conversion for two-digit sectors between the different classifications can be obtained in a rather straightforward manner, whereas this is not possible for four-digit sectors. For this reason, a two-digit sector index has been created and used to deflate the labor input.

B Sector classifications

Product Groups to be used in 2006 Survey of Business Enterprise R&D

Product group code (to enter on questionnaire)	Description	SIC 2003 (for reference)*
A	**Agriculture, Hunting** and **Forestry**; Fishing	01, 02, 05
B	**Extractive Industries** including solids, liquids and gases	10, 11, 12, 13, 14
C	**Food products** and **beverages**; Manufacture of **tobacco** products	15, 16
D	**Textiles** and **clothes**; Tanning and dressing of **leather**; Manufacture of luggage, handbags, saddlery, harness and footwear	17, 18, 19
E	**Wood** and products of wood and cork; Manufacture of articles of straw and plaiting materials. Pulp, **paper** and paper products; **Publishing, printing** and **reproduction** of **recorded media**	20, 21, 22
F	**Refined petroleum products** and coke oven products; **Processing of nuclear fuel**	23
G	**Chemicals,** chemical products and man-made fibres (excluding manufacture of pharmaceuticals, medical chemicals and botanical products)	24 (excl. 24.4)
H	**Pharmaceuticals**, medical chemicals and **botanical** products	24.4
I	**Rubber** and **plastic** products	25
J	Other **non-metallic mineral** products	26
K	**Basic iron and steel** and **ferro-alloys (ECSC)**; Manufacture of tubes; Other first processing of iron and steel and production of **non-ECSC ferro-alloys**; Casting of iron; Casting of Steel	27.1, 27.2, 27.3, 27.51, 27.52
L	Basic **precious** and **non-ferrous metals**; Casting of light metal; Casting of other non-ferrous metal	27.4, 27.53, 27.54
M	**Fabricated metal products,** except machinery and equipment	28
N	**Machinery** and **equipment** not elsewhere classified	29
O	**Office machinery** and **computers**	30
P	**Electrical machinery** and apparatus not elsewhere classified	31
Q	**Radio, television** and communications equipment apparatus	32
R	**Medical precision and optical instruments,** and appliances for measuring, checking, testing, navigating and other purposes	33
S	**Motor vehicles,** trailers and semi-trailers; Parts and accessories for motor vehicles and their engines	34

* Standard Industrial Classification of Economic Activities 2003, a publication of the Government Statistical Service.

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Product Groups to be used in 2006 Survey of Business Enterprise R&D

Product group code (to enter on questionnaire)	**Description**	**SIC 2003** (for reference)*
T	**Railway and tramway locomotive and rolling stock;** Motorcycles and **bicycles;** Other **transport equipment** not elsewhere classified	35.2, 35.4, 35.5
U	Building and repairing of **ships** and **boats**	35.1
V	**Aircraft** and spacecraft	35.3
W	**Furniture**; **Jewellery** and related articles; **Musical instruments; Sports goods; Games and toys; Miscellaneous manufacturing** not elsewhere classified	36
X	Recovered secondary raw materials, **recycling**	37
Y	**Electricity, gas** and **water** supply	40, 41
Z	**Construction**	45
AA	**Wholesale and retail trade;** Repair of motor vehicles, motorcycles and personal household goods; Hotels and restaurants	50,51,52,55
AB	**Transport** and **Storage**	60,61,62,63
AC	**Post** and **telecommunications**	64
AD	**Financial** intermediation; **Real estate** and renting; **Legal,** accounting, book-keeping and auditing activities; Tax consultancy; **Market research** and public opinion polling; **Business and management consultancy;** Holdings; **Advertising;** Labour **recruitment** and provision of **personnel; Investigation** and **security activities; Industrial cleaning;** Miscellaneous business activities not elsewhere classified; **Architectural** and **engineering** activities and related technical consultancy; **Technical testing** and analysis	65,66,67 70,71,74
AE	**Computer** and related activities, including **software** consultancy and supply	72
AF	**Research** and **development services** If you choose product group code AF please use the comments box on the back of the form to give a brief description of your R&D activity.	73
AG	**Public administration**; Education, Health, community, social and personal services; sewage and refuse disposal, sanitation and similar activities; **Private households** with employed persons, **Extra-territorial** organisations and bodies.	75 to 99

* Standard Industrial Classification of Economic Activities 2003, a publication of the Government Statistical Service.

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This table has been provided by the UK Data Service as part of the information on BERD 2006 Survey Questionnaire in the guidance notes for Study 6690. This information can be found online at http://doc.ukdataservice.ac.uk/doc/6690/mrdoc/pdf/6690questionnaires.pdf

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Chapter 4
Conclusion

In this thesis, I explored the effectiveness of tax incentives on stimulating private R&D, followed by a discussion of the relationship between R&D spending with productivity in manufacturing sectors, and presented estimates of the elasticity of output with respect to the R&D input. R&D input in this context meant both the in-house R&D conducted by one or more units within the firm and also the R&D that is carried out by neighboring firms in technology and product space.

The quasi-experiments in Chapter 1 and Chapter 2 both found a significant positive effect of tax incentives on private R&D spending. In Chapter 1, using the BERD repeated cross-section data, I found that the enterprises which became eligible for the R&D Tax Relief for Large Companies in 2002 increased their R&D spending by around 18 percent in comparison to the control group, whose eligibility did not change throughout the sample period. The increase in R&D spending by the treated enterprises has been found to be permanent and close to full effect was materialized shortly after the introduction of the policy. I presented robustness checks for the difference-in-difference estimates to the possible anticipation effects which may have arisen because of the early announcement of the policy. I found that the results are robust to the removal of the years after the announcement of the policy and before its implementation. Sector-specific difference-in-differences coefficients did not seem to differ significantly from each other, possibly suggesting that broad-based policies are equally effective for high tech and low tech sectors. At the same time, this pattern may have been observed because of the small number of observations that fall in each of the sectors.

It is possible to translate the difference-in-difference estimates to a user cost elasticity and compare them with the estimates from structural models in the existing literature. In Chapter 1, I explained the assumptions that underlie such conversion. The 18 percent differential increase in R&D spending by the treated firms found in Chapter 1 roughly translates to a user cost elasticity of around -1.4, which is a little larger in magnitude than the structural estimates found in the literature. I argue that because of a possible simultaneity bias between tax price and R&D, we may expect to observe point estimates that are larger in magnitude when we are better able to identify the impact of the tax incentive policy through a quasi-experimental set up as the ones provided in Chapter 1 and Chapter 2 of this thesis. The simultaneity arises because companies can reduce their tax liability by spending more on R&D and move to a lower statutory tax bracket.

In Chapter 2, we found that the companies whose status changed from large to SME for the purpose of the R&D Tax Relief, and hence who became eligible for a more generous tax incentive increased their R&D intensity by around 12 percentage points, amounting roughly to a doubling of R&D intensity for the treated firms. Both the policy set up and the data used in Chapter 2 has several advantages over that available in Chapter 1. First of all, Chapter 2 used the universe of corporation tax returns, and we were able to observe both the claimants of the R&D Tax Relief and their precise tax positions, which is a data set that had never been used before in the R&D context. Second, we were able to observe the same companies over time, which allowed us to exploit the panel dimension of the data set. Third, the policy reform of interest took place 6 years after the implementation of the large company scheme, leaving an adequate amount of time for learning and take up. Anecdotal evidence from HM Treasury and HMRC consultation meetings and our discussions with claimants supported this view. Further work on this topic may make more use of the corporation tax returns data and explore where in the distribution of R&D activity the largest effect is observed. Preliminary work in this area finds that the largest spenders in R&D are the ones that benefit the most from more generous tax incentives.

In both Chapter 1 and Chapter 2, for comparability between treatment and control groups, estimation samples have been limited to the narrow size bands defined around the eligibility threshold for the SME scheme. The size bands were determined with the aim of meeting the common trends assumption required for identification in difference-in-differences, which then resulted in sample sizes that are relatively small, hence lowering the power of detecting the effect of the policy. In Chapter 1, the stratified sampling procedure of the BERD data set in the size bands of interest was another reason for having a smaller sample size than would have been desirable. In Chapter 2, the data is available on all beneficiaries of the R&D tax incentives, but the corporation tax returns data was missing some of the benecifiaries' information from HMRC's Specialist R&D Units. Future work aims to address this issue regarding the small sample sizes using the additional information from Specialist R&D Units and more recent years' data, which is expected to be made available in the HMRC Datalab.

The ultimate goal of governments in raising private R&D and innovation is to enhance overall productivity. My aim in Chapter 3 was to establish this connection and show the response of manufacturing output to various different types of R&D inputs; those that are internal to the reporting unit, then internal to the firm but external to the reporting unit and finally the R&D that is external to the firm, performed by neighboring firms in technology and product space. Using non-imputed long form information in the BERD data set, I was able to address important measurement issues and obtain estimates of the elasticity of output with respect to R&D inputs using static models. I showed that the mismeasurement of inputs caused by R&D inputs being counted under conventional labor and materials resulted in the underestimation of the impact of the firms' own R&D on productivity. After the correction, I found elasticity estimates of output with respect to own R&D around 2-3 percent. For the units that only concentrate on production and have no R&D activity, the R&D performed in other parts of the enterprise group has been found to be productive. In terms of addressing the question about whether positive technology spillovers exist between neighboring firms in technology space, I found mixed evidence, which suggests that future work may focus on refining the measures of external R&D by using patent ownership and citation data.

The detailed data sets used in this study provide valuable micro level information on R&D and productivity, which may be used in future work by researchers who conduct empirical work in these fields. As a future step in developing this work, I aim to explore the more direct connection between R&D tax incentives and productivity, in the sense of differentiating between productive and unproductive R&D generated as a result of tax incentives. In the future, it is expected that the legal framework governing the administrative micro data sets will be amended, which would then allow for linking HMRC Corporation Tax Returns data with the ONS BERD data for a more detailed analysis of such connections involving complementarities between R&D that qualifies for the tax incentive as opposed to R&D that does not[1]. In the shorter term, I also consider merging the HMRC data set with intellectual property information to evaluate the policy effect on 'innovation outputs' in addition to the 'innovation input'.

[1]Consultations for merging ONS, HMRC and other data collected by public bodies are ongoing by the UK Government.

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