INNOVATION & RESEARCH CAUCUS

BEYOND THE GOLDEN TRIANGLE:

Evaluating the impact of government R&D support on firm-level innovation inside and outside of the Oxford-Cambridge-London region

IRC Report No: 040

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You are also welcome to email us if you have any questions about this report or the work of the IRC generally: info@ircaucus.ac.uk

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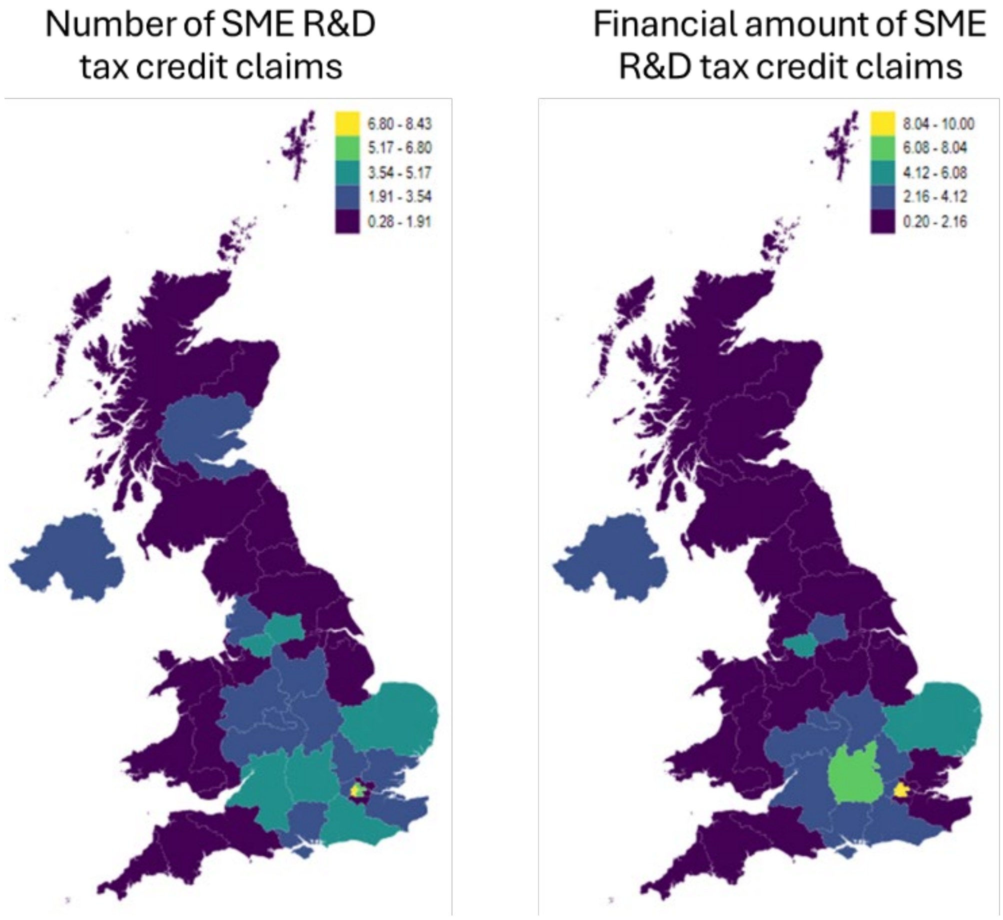
Executive Summary

Background

This project examines the impact of Research and Development (R&D) tax credits on the innovation performance of Small and Medium-sized Enterprises (SMEs). The analysis focuses on comparing SMEs based in the UK's so-called 'Golden Triangle', located in the South-East of England between Oxford, Cambridge, and London, with SMEs based in the UK's other regions. We examine whether the effectiveness of R&D tax credits for SMEs is significantly influenced by being located in the Golden Triangle. We focus on the Golden Triangle because significant research shows it has received a disproportionally large and sustained level of public R&D investment over several decades. This has developed a critical mass of R&D infrastructure such as Universities, science labs and clusters of high-tech firms, which is largely unavailable to firms in other UK regions.

Firms based in the Golden Triangle may be able to combine these unique location-specific advantages with the support provided through R&D tax credits to achieve superior innovation performance. A key concern for policy is that this may place firms in the UK's other regions at an implicit disadvantage, inadvertently widening regional R&D inequality. As shown in Figure 1, R&D tax credit claims for SMEs are highly concentrated in the geographical area broadly defined as the Golden Triangle. According to Figure 1, not only do many more SMEs submit R&D tax credit claims in the Golden Triangle, but the value of these claims is much higher.

Notwithstanding this concern from a policy perspective, evidence on the region-specific effectiveness of R&D tax credits is currently lacking. This is a significant gap in knowledge for the UK research and innovation system. R&D tax credits are by far the largest R&D support targeted at firms, accounting for approximately £7 billion per year. For scale, this equated to approximately 14% of total UK business expenditure on R&D (£50 billion in 2023). In terms of the industrial base, we focus on SMEs because much research argues that they are a key engine of radical innovation within the UK economy, as they seek to challenge larger incumbent firms and compete internationally. However, previous studies also highlight that SMEs face the most acute obstacles to innovation and are thus a key target for R&D policy support.



Source: HMRC Research and Development Tax Credits Statistics 2023. Note: The R&D tax credit claim amount for Inner London West is capped at 10, as this is a significant outlier which distorts the rest of the map (the true number is 16.7).

Figure 1: Number and financial amount of SME R&D tax credit claims by NUTS2 region

Findings

The project uses detailed data on SMEs from the UK's Longitudinal Small Business Survey (LSBS), collected annually by the Department for Business and Trade (DBT). Through thorough econometric analysis, our results show that:

- SMEs located in the Golden Triangle do not derive any significant additional innovation benefit simply by virtue of their location (i.e. overall innovation performance is similar for SMEs both within and outside of the Golden Triangle).
- In the UK overall, R&D tax credits are highly effective at driving SME radical innovation (i.e. both within and outside of the Golden Triangle).
- Importantly, R&D tax credits are more effective at driving radical innovation for SMEs within the Golden Triangle, relative to SME R&D tax credit recipients located in other

UK regions (i.e. while the impact is positive throughout the UK, it is significantly higher in the Golden Triangle).

These results suggest that R&D tax credits are a highly effective Government R&D support for achieving desired policy outcomes. The fact that the impact occurs for radical innovation in SMEs is particularly important, as this is a key policy target which supports a competitive and resilient research and innovation system. Considering that the positive effects of R&D tax credits vary significantly by region highlights the importance of innovation policy that embeds a focus on clustering and agglomeration.

Actionable insights for policy

At approximately £7 billion per year, the UK's R&D tax credit programme costs a significant amount for the public purse in terms of tax receipts forgone. It has also come under criticism for the occurrence of fraud and error, where firms submit tax relief claims for activities other than those strictly defined as R&D. Issues such as these motivate calls to reduce the level of support available through the R&D tax credit, and/or make the process of claiming R&D tax credits more rigorous for firms (e.g. through more detailed audit checks). The findings from our research suggest that these calls may be misplaced, and should be handled with great care. Our analysis shows that, on average, R&D tax credits are highly effective at driving SME radical innovation. Increasing the complexity of the claiming system, or reducing the level of support, could jeopardise these positive and hard-to-achieve policy outcomes.

Our results for R&D tax credits in the Golden Triangle seem to confirm a suggestion which is prominent in previous academic studies and policy reports: SMEs located in the Golden Triangle can leverage location-specific advantages to supercharge the effectiveness of Government R&D support, in a way that is not available to SMEs located in other UK regions. SMEs located outside of the Golden Triangle may require specific tailored policy interventions which enable them to leverage local advantages, as well as compensating for certain key factors which are unavailable in their local context.

Notwithstanding this key point, the positive aspatial benefits of R&D tax credits should be appreciated in the UK research and innovation system. When our results are considered in combination with data on UK regional R&D investment patterns (see Figure 1), the following insights become clear:

- The number of R&D-active SMEs located outside of the Golden Triangle is lacking.
- For the relatively small number of R&D-active SMEs in these ‘other’ regions, their R&D spending is relatively low compared to SMEs in the Golden Triangle.

In this context, an additional key role for policy appears to be the following:

- Increasing the number of R&D-active SMEs located outside of the Golden Triangle, so they can benefit from R&D tax credit claims, as our results show this is a highly effective R&D support.
- Developing the R&D capacity of the already R&D-active SMEs located in the UK’s other regions, so that they can claim R&D tax credits to the same level as SMEs located in the Golden Triangle.

This suggestion is based on a combination of our results, and the data underpinning Figure 1, which shows that 56% of the total cost of R&D tax credit claims takes place in the Golden Triangle. These points can be interpreted as meaning that while all firms derive an R&D and innovation benefit from the highly effective R&D tax credit programme, firms in the UK’s other regions do not derive the same level of benefits as firms operating in the Golden Triangle. A key means of inducing SMEs in non-Golden Triangle regions to become R&D active and increase their R&D investments to a sufficient level may be through targeted R&D grants, that have a specific goal of building place-based R&D capacity. Targeted R&D grant programmes can embed place-based policy into their design, and focus on SMEs outside of the Golden Triangle in an effort to close regional R&D performance gaps.

1. Introduction

"The Government have set a very ambitious target of R&D being 2.4% of GDP. It is a good thing. I do not believe we have any chance of achieving that if all we invest in is a triangle bounded by Oxford, Cambridge and London."

– Sir John Kingman (2018)
Oral evidence to the House of Commons Science and Technology Committee
Pre-appointment hearing for UK Research and Innovation (UKRI) Chair

Much evidence suggests that public Research and Development (R&D) support plays a key role in driving firms' innovation (Dimos et al. 2024; Lenihan et al. 2025; Liu et al. 2025; Lee & Lembcke 2025). However, there is significant debate over the effectiveness of R&D subsidies for firms located in regions with different characteristics, such as above- and below-average R&D and innovation intensities (Roper et al. 2025; Mulligan 2024). This is particularly important for the UK's so-called 'Golden Triangle' between Oxford, Cambridge, and London. This region plays a unique and crucial role for R&D-driven innovation within the UK economy (Tracey & Williamson 2023).

Notwithstanding this important role with the UK's R&D system, several studies argue that the Golden Triangle has attracted a disproportionately high level of public R&D investment over several decades, resulting in outsized innovation-intensive private sector agglomerations (Mueller et al. 2012; Kempton et al. 2021). As a result, firms located in the Golden Triangle benefit from knowledge spillovers which are unavailable to firms in other regions (Benneworth 2007; Helmers & Rogers 2015; Jelfs & Smith 2021). These knowledge spillovers may in-turn enhance the effectiveness of public R&D support for firms in this region (Alecke et al. 2021; Barzotto et al. 2019). As a knock-on consequence, the already existing R&D and innovation performance gap between the Golden Triangle and the rest of the UK may continue to widen (Perry 2007; Martin et al. 2022). To examine this issue, our study provides the first evaluation of what impact public R&D support has on the innovation performance of firms located in the Golden Triangle vs. firms in other UK regions.

The 2023 UK government R&D spending report makes the scale of this issue clear, showing that 52% of all UK R&D investment was concentrated within the Golden Triangle (Panjwani et al. 2023). Forth and Jones (2020) have estimated that rebalancing

R&D investment across UK regions would cost an additional £4 billion per year. Indeed, these authors note that "the geographical mismatch between the location of public sector spending on R&D and private sector spending on R&D implies that potential spillover benefits from publicly funded research are being lost" (Forth & Jones 2020, p. 26). However, policy solutions to this issue are far from clear. In the UK, research funding is allocated to universities and research teams according to the Haldane principle (Lee 2017). This states that support should go to the best science, regardless of other concerns such as regional location. This makes it difficult (and perhaps impossible) to recreate equivalent knowledge spillovers outside of the Golden Triangle, as future funding follows past in a self-reinforcing mechanism (Helmers & Rogers 2015).

Moreover, Flanagan and Wilsdon (2018, p. 13) have questioned whether UK policymakers will "really have the appetite to take resources from the Golden Triangle". In response to this, UK Research and Innovation (UKRI), the national agency responsible for allocating R&D funding to firms, has recently adopted a 'place' agenda. This new focus acknowledges that "[r]outes to impact might vary for different places", leading to the need for targeted region-specific support (SQW 2022, p. 11). However, despite the importance of this issue, a recent review of existing literature by Lee (2024) concluded that there is little persuasive evidence on regional differences in how government R&D support impacts firm-level innovation. This lack of knowledge hinders understanding of how to address regional R&D imbalances with firm-level policy interventions.

Bearing in mind the above points, this report contributes to current debates first by examining whether regional agglomerations of R&D infrastructure significantly improve the effectiveness of government support for firm-level R&D. Existing research suggests that firms located in agglomerations such as the Golden Triangle benefit from knowledge spillovers, which are unavailable to firms in other regions (Benneworth 2007; Helmers & Rogers 2015; Jelfs & Smith 2021). However, the literature currently does not provide sufficient evidence on whether these knowledge spillovers may in-turn enhance the effectiveness of public R&D support (Alecke et al. 2021; Barzotto et al. 2019). This is a crucial issue within the UK for both academics and policymakers, where the role of 'place' has recently been emphasised as crucial in Government R&D policy (SQW, 2022). Moreover, our analysis will provide insights which may be applicable internationally, for countries such as Germany, Korea and China which also feature major regional R&D imbalances.

This report's second contribution focuses on the region-specific impacts of R&D tax credits, a top-down, one-size-fits-all policy instrument, that is aspatial in nature. R&D tax credits play a major role in the UK economy, accounting for two thirds of all public R&D support provided to firms (Roper et al. 2024). However, no previous study has examined how the effectiveness of such an important one-size-fits-all R&D policy instrument varies depending on region-specific factors (Lee & Lembcke 2025). This is an important gap in knowledge, given the level of public R&D funding at stake. In previous research, Vanino et al. (2019) have shown that UK government-supported firm-university research collaborations have a stronger effect in more R&D intense regions, and no effect whatsoever in the least R&D intensive regions. Similarly, Mulligan (2024) shows that innovation subsidy recipients located in less innovation-intense regions significantly underperform matched-unsubsidised firms in higher innovation-intensity regions. The lack of understanding regarding regional variation in the impact of R&D tax credits remains a key gap in the literature.

To implement our analysis, we draw on the Longitudinal Small Business Survey (LSBS), which is collected annually by the UK Department for Business and Trade (DBT). The final dataset is an unbalanced panel, tracking approximately 4,500 firms between 2015-2023, producing circa 25,700 firm-year observations. Beyond its large size, the LSBS has three features which make it ideal for addressing our research question:

1. It captures whether firms claim R&D tax credits. Relative to other R&D subsidies such as competitive direct grants, R&D tax credits are neutral in their allocation. This means that once firms perform R&D, they qualify to claim the tax credit support. In this way, focusing on the R&D tax credit provides a means of examining the interaction between R&D subsidies and potential Golden Triangle spillover effects, free from issues such as cherry-picking winners by funding agencies (Mulligan et al. 2022).
2. The LSBS provides granular detail on firms' regional location, sub-dividing England into 39 Local Enterprise Partnership (LEP) regions, which is crucial for defining the Golden Triangle with accuracy.

3. Finally, the LSBS focuses solely on Small and Medium-sized Enterprises (SMEs). This is important because SMEs are a crucial engine of innovation, and the focus of significant policy support (Roper & Hewitt-Dundas 2017; Ipinnaiye et al. 2025). In addition, SMEs usually only have one location in a country, while larger firms tend to have multiple sites. This means that for larger firms, information on R&D tax credit claims and innovation activity could be misattributed to where a firm is headquartered, as opposed to the local site where the activity took place. The LSBS helps our analysis overcome this issue to a greater extent than is possible with other datasets.

Turning to methods, the vast majority of previous empirical studies examining R&D subsidies have used firms' regional location as a control variable in econometric analysis. However, such analyses seek to estimate the average effect of R&D subsidies, and thus provide little insight on regional differences. In this way, previous research may inadvertently mask potential regional inequalities in the effectiveness of R&D subsidies. To overcome this issue, our analysis adopts a two-stage process. In stage one, we use propensity score matching to create a matched sample of firms, with the only differentiating factor being firms' location within the Golden Triangle or the rest of the UK. This sample provides the platform for a fair comparison of like-with-like between the Golden Triangle and other UK regions. In stage two, we implement a difference-in-differences regression on the matched sample, which controls for unobserved heterogeneity that is not accounted for in the stage one matching. This analysis uses interaction variables to examine the effectiveness of R&D tax credits for firms located inside and outside of the Golden Triangle.

Results from this analysis show three key overall findings:

1. SMEs located in the Golden Triangle do not derive any significant additional innovation benefit simply by virtue of their location.
2. R&D tax credits have a positive and significant impact on SME radical innovation both within and outside of the Golden Triangle.
3. R&D tax credits are more effective at driving radical innovation for SMEs within the Golden Triangle, relative to SME R&D tax credit recipients located in other UK regions (i.e. while the impact is positive throughout the UK, it is significantly higher in the Golden Triangle).

These results suggest that R&D tax credits are a highly effective Government R&D support for achieving desired policy outcomes. The fact that the impact occurs for radical innovation in SMEs is particularly important, as this is a key policy target which supports a competitive and resilient research and innovation system. However, SMEs located outside of the Golden Triangle may require specific tailored policy interventions which enable them to leverage local advantages, as well as compensating for certain key factors which are unavailable in their local context.

The remainder of this report is organised as follows. Section 2 describes the data and methodology used to examine the impact of R&D tax credits on SME innovation performance inside and outside of the Golden Triangle. Section 3 presents and discusses the results from our analysis. Finally, Section 4 provides a conclusion to the report and details actionable insights for UK research and innovation policy which flow from our findings.

2. Data

This report makes use of the UK Longitudinal Small Business Surveys (LSBS). The LSBS is a large-scale survey of the owners and managers of UK SMEs (defined as firms with fewer than 250 employees), commissioned by the Department for Business and Trade (DBT). Our sample period is from 2015, when the LSBS survey began, to 2023, the most recent year available up to the point of publication for this report. The LSBS has been used in several previous studies to examine SME innovation in the UK economy (e.g. Cowling et al. 2024a; 2024b, 2025; Tiwasing et al. 2023). The LSBS captures a wide variety of relevant firm-level characteristics, such as innovation, exports, financing, and training. The sample of SMEs included each year is selected using a complex stratification method across sectors, firm sizes, and nations (England, Scotland, Wales, Northern Ireland). Weights are assigned to each firm so that the data are representative of the UK's SME population.

A key advantage of the LSBS relative to other UK business innovation surveys is that it is a panel dataset, which tracks the same firms over time. In terms of evaluating R&D tax credits, this feature enables this report to examine firms' innovation behaviour before, during and after they claimed R&D tax relief. As such, the current report is able to conduct a highly robust analysis. In this way, it is crucial for our study to track firms which claimed an R&D tax credit (or did not claim) for a minimum of three observations, which fall in a specific order over the sample period:

- The year where firms claimed (or did not claim) an R&D tax credit
- At least one-year post-R&D tax credit claim (or non-claim) where we measure innovation outcomes
- At least one year pre-R&D tax credit claim (or non-claim) where we measure all control variables

More detail is given on the specifics of our data set-up below in the context of the LSBS. However, the above summary points highlight the overall picture. While we require a minimum of three observations on each firm to be usable in the analysis, in reality, we have many more observations than this for most firms. As such, our final analysis consists of:

- 4,551 unique firms
- 25,763 firm-year observations

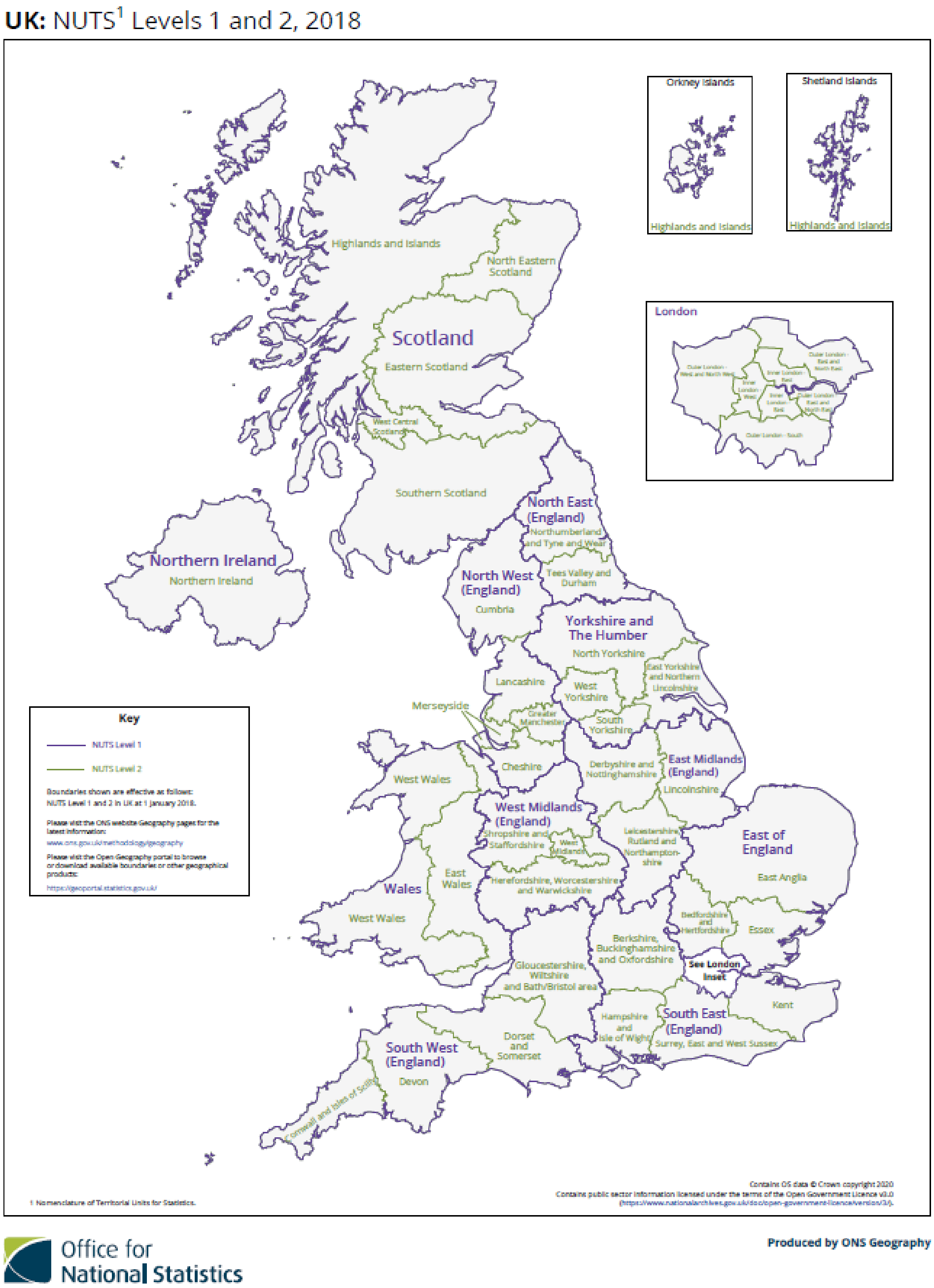
These numbers compare very well with those used in previous studies, and form the basis for a robust analysis of the impact of R&D tax credits on SME innovation both within and outside the Golden Triangle.

2.1. Defining the Golden Triangle

A crucial issue for our study is the definition of the Golden Triangle. While this term is commonly used in the academic literature (Mueller et al. 2012; Helmers & Rogers 2015; Kempton et al. 2021; Jelfs & Smith 2021) and government policy reports (DSIT 2023; HM Treasury 2025), there is no strict or universally accepted definition. Colloquially, the Golden Triangle can be taken to mean the region on a map bounded by the University of Cambridge, University of Oxford, and Imperial College London (see e.g. Huggins & Kitagawa 2011). However, in practice, the definition used in a given analysis typically relies as much on data availability as theory underpinning the concept. In this way, most studies have defined the Golden Triangle as the NUTS1 or NUTS2 regions which contain the above Universities, as well as adjacent regions which make theoretical sense to include:

- London
- South East
- East of England

Figure 2 provides a map of the UK indicating the NUTS1 and NUTS2 regional definitions.

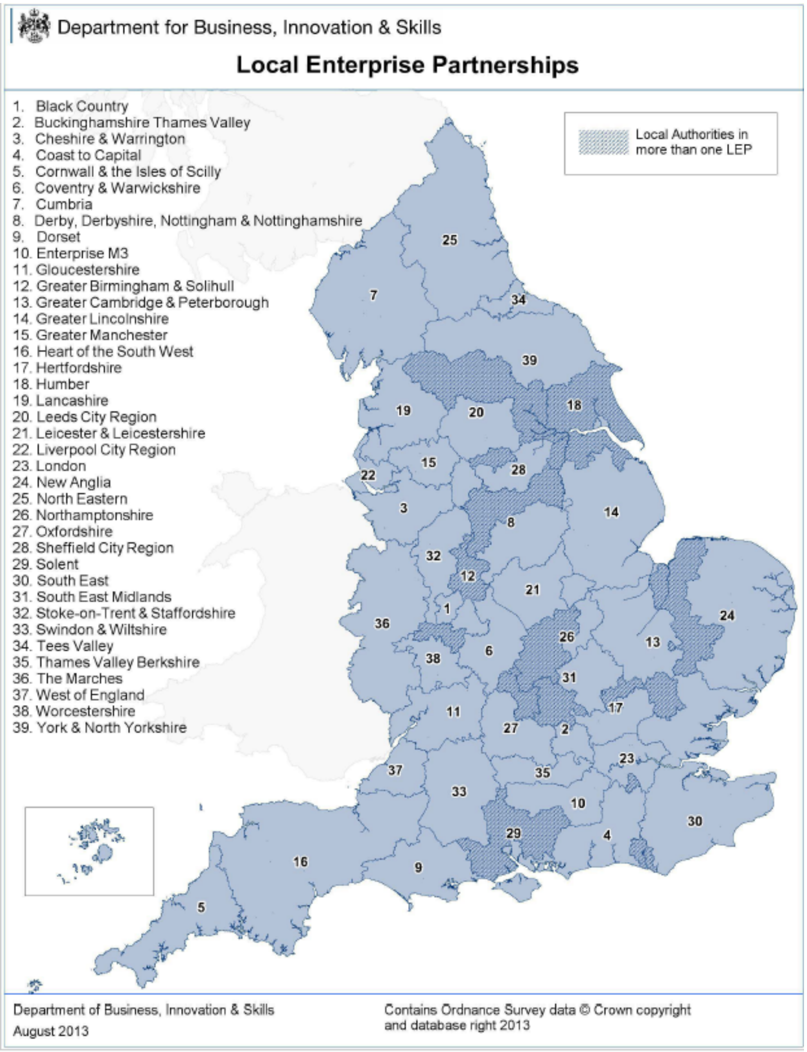


Source: https://geoportal.statistics.gov.uk/documents/01bac08b01874aa6820d2064ed5d4742/explore

Figure 2: Map of UK NUTS1 and NUTS2 regions

Given the lack of a strict theoretical or statistical rationale for defining the Golden Triangle in a certain way, our report adopts a pragmatic approach. The LSBS data enables us to run different analyses that define the Golden Triangle on a spectrum from 'narrow' to 'broad'. The narrow definition includes the fewest possible regions that could constitute the Golden Triangle, while the broad definition includes all regions adjacent to the narrow definition, with each definition in between gradually adding regions in order of potential importance.

The LSBS includes a location variable which captures whether firms in England were located in one of 39 Local Enterprise Partnership (LEP) regions. The UK LEPs are detailed in Figure 3. LEPs were created in 2010/2011 as voluntary, non-statutory, business-led partnerships between local authorities and private-sector leaders to drive local economic growth across England. The policy was announced in 2010 as a replacement for abolished regional development agencies, with a remit to agree local growth priorities and negotiate funding with central government. LEPs were explicitly positioned to combine private-sector leadership with public accountability to set strategic economic plans, attract investment and deliver local-growth programmes. In the 15 years since their formation, LEPs have become conduits for multiple funding streams and for business-facing services, inward-investment advice and sector strategies. Despite some issues with uneven implementation, the National Audit Office (2016; 2019) has suggested that the LEP model has become central to England's place-based economic governance. Importantly for the current study, LEPs are frequently used in academic research to identify firms' regional location (see e.g. Cowling et al. 2024a; Cowling & Brown 2024; Tiwasing et al. 2023; Harras & Moffat 2022; 2025).



Source: https://www.gov.uk/government/publications/local-enterprise-partnerships-map

Figure 3: Local Enterprise Partnerships (LEPs) in England

Using the LEPs defined in Figure 3, we build our measures of the Golden Triangle from narrow to broad using the following definitions:

- Narrow Golden Triangle definition includes the following LEPs: 1) Greater Cambridge & Peterborough; 2) London; 3) Oxfordshire.
- Broad (1) Golden Triangle definition includes the following LEPs: 1) Greater Cambridge & Peterborough; 2) London; 3) Oxfordshire; 4) Enterprise M3; 5) South East Midlands.

- Broad (2) Golden Triangle definition includes the following LEPs: 1) Greater Cambridge & Peterborough; 2) London; 3) Oxfordshire; 4) Enterprise M3; 5) South East Midlands; 6) South East.
- Broad (3) Golden Triangle definition includes the following LEPs: 1) Greater Cambridge & Peterborough; 2) London; 3) Oxfordshire; 4) Enterprise M3; 5) South East Midlands; 6) South East; 7) Thames Valley Berkshire; 8) Thames Valley Buckinghamshire; 9) Coast to capital.

As is clear from Figure 3, the above definitions include the adjacent regions to the 'narrow' Golden Triangle definition. Within the overall data structure discussed above, the number of firms who claimed an R&D tax credit are as follows:

- 462 firms who claimed an R&D tax credit
- 2,745 firm-year observations for firms who claimed an R&D tax credit
- 50 firms who claimed an R&D tax credit in the Golden Triangle (narrow definition; this number increases as the definition broadens)
- 299 firm-year observations for firms who claimed an R&D tax credit in the Golden Triangle (narrow definition; this number increases as the definition broadens)

The above indicates that we have on average approximately 6 observations per usable R&D tax credit claimant located in the narrow definition of the Golden Triangle. This sample size in the key category for our analysis is sufficient to conduct a robust and detailed analysis.

2.2. Innovation outcome

The LSBS captures SME innovation through a series of binary variables. Product innovations can be new to the firm, which is known as incremental innovation, or new to the market, which is referred to as radical innovation (OECD/Eurostat 2018). The focus of this study is on the potential influence of proximity-based knowledge spillovers within the R&D-intensive Golden Triangle for SMEs. While incremental innovation can frequently occur in the absence of R&D spending, several studies suggest that R&D is a key input into radical innovation (Beck et al. 2016; Leung & Sharma 2021; Foucart & Li 2021). Therefore, we focus on SMEs' radical innovation as our main innovation outcome measure. Figure 4 below summarises the level of overall SME product innovation (i.e. incremental and radical) in the UK by LEP region, as well as radical product innovation. Figure 4 highlights that there is a significant innovation spike in the Golden Triangle area. This supports our decision to focus on this region as unique within the UK in terms of generating knowledge spillovers which are unavailable to firms in other regions.

2.3. R&D tax credit: UK context and survey definition

The UK R&D tax credit scheme was introduced in the year 2000 for SMEs only. Since this date, it has evolved significantly to become a major feature of the UK research and innovation system. Figure 5 highlights the growth of the R&D tax credit programme for SMEs. This shows the rapid growth phase from 2012-2013, when the scheme was redesigned to also target R&D in larger firms and enable larger R&D tax credit claims by SMEs. During this growth period, SME claims went from under £1 billion to over £5 billion in a decade.

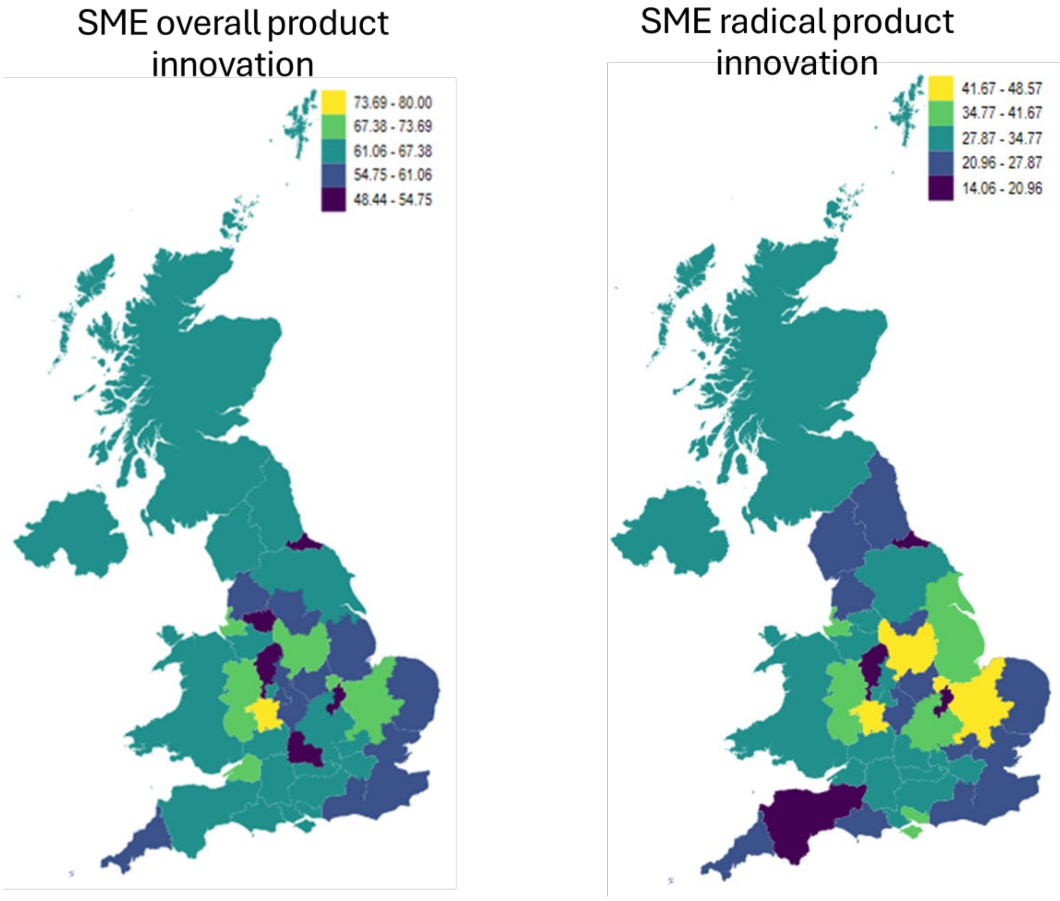
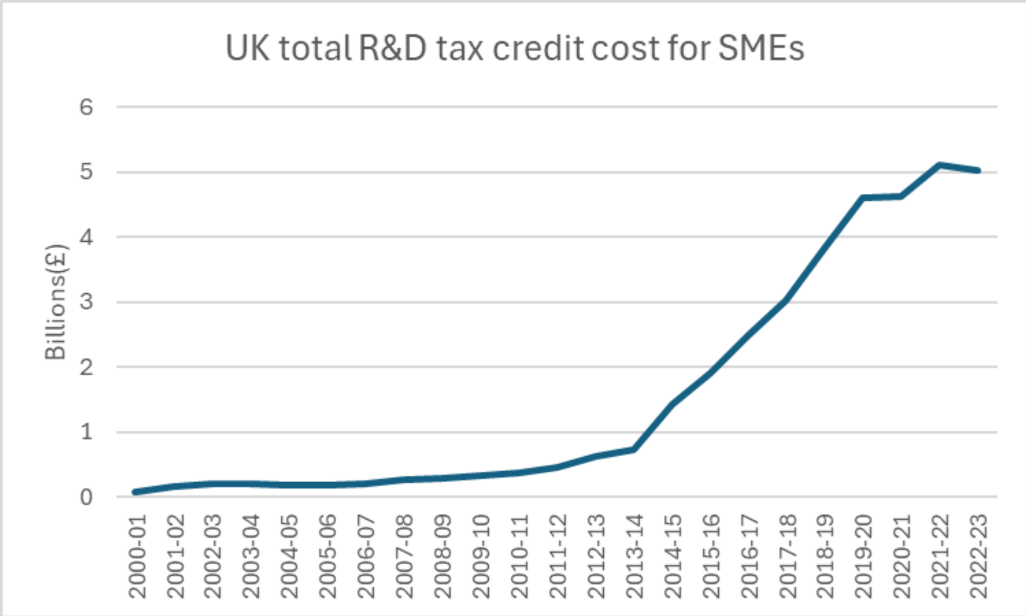


Figure 4: SME overall product innovation and radical product innovation by LEP region



Source: HM Revenue & Customs (https://www.gov.uk/government/statistics/corporate-tax-research-and-development-tax-credit). Note: HMRC definition for SMEs is firms with fewer than 500 employees, while the LSBS definition is firms with fewer than 250 employees.

Figure 5: Evolution of the SME R&D tax credit programme over time

In practice, for every £1 SMEs spend on eligible R&D, the firm can treat it as £2.30 for tax purposes. This functions by adding an additional 130% deduction on top of the normal 100% deduction, creating a total tax deduction of 230%. The benefit could be taken either as a reduction in corporation tax for profit-making SMEs, or, importantly, as a cash payment from HMRC for loss-making SMEs. Below provides two indicative examples:

- A profit-making SME: If a company spent £100,000 on qualifying R&D, it could deduct £230,000 from its taxable profits. At a 19% corporation tax rate, that generated a tax saving of £43,700, means the additional benefit from the incentive would be about £24,700 above what the business would normally save without the scheme.
- A loss-making SME (cash repayment): The same £100,000 spend could be treated as a £230,000 tax loss and surrendered to HMRC for a cash credit at a rate of 14.5%. This would result in a cash payment of £33,350, effectively giving the company around one-third of its R&D spending back in cash.

In simple terms, during this period the scheme typically reduced the real cost of R&D by 25-33%, depending on whether the company was profit-making or loss-making. In our sample, the percentage of R&D tax credit claims by SMEs in each LEP region is summarised in Figure 6.

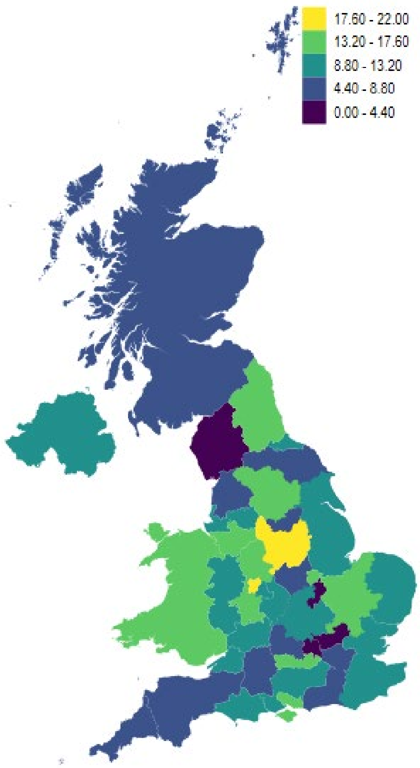


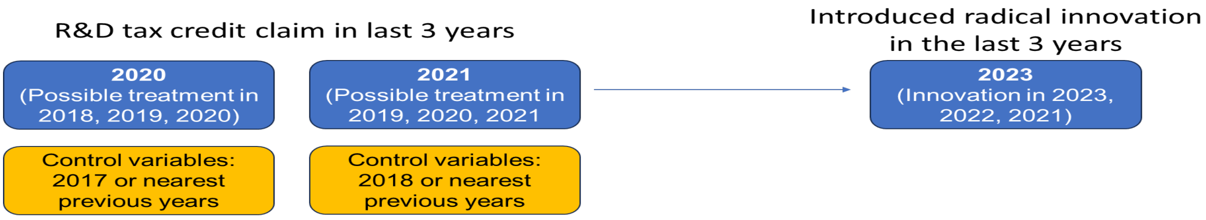
Figure 6: R&D tax credit claims by SMEs in each LEP region and UK nation

In contrast to Figure 4, Figure 6 shows that the geographical distribution of R&D tax credits claims is more even in the UK when compared to innovation outcomes. In addition, as noted above, the LSBS is collected in a way so as to be representative of the UK SME population on the basis of region, firm-size, and sector. Therefore, Figure 6 likely reflects the aspatial nature of the R&D tax credit, in that it is available to all R&D-active firms.

2.4. Data set-up: Timing of key variables

The key variables for this report capture whether firms introduced a radical innovation, and whether firms claimed an R&D tax credit. When seeking to conduct an impact analysis, the timing of these variables is crucial. R&D tax credits are claimed on R&D spending which has typically already occurred (i.e. the firm has to make the investment before it can submit a claim). Transforming R&D spending into radical innovation can take a significant time lag, as this usually involves more input than incremental innovation (Liu & Xu 2025). Therefore, it is crucial that our study builds in a time lag between when firms claim an R&D tax credit, and when we measure any potential resulting innovation activity.

In addition to the above, the LSBS has some unique features for how innovation and R&D tax credit claims are measured, which must be built into any analysis. As is common in many innovation surveys, both variables are measured over a three-year period. This means that in a given year, firms are asked whether they have claimed an R&D tax credit in the last three years. For example, if a firm completed the LSBS survey in 2023 and indicated they claimed an R&D tax credit, this claim could relate to 2023, 2022, or 2021. Firm-level innovation is measured in the same way in the LSBS. In these circumstances our analysis must avoid the most simple and intuitive data set-up, where R&D tax credit claims are measured in one year, and innovation outcomes are measured in the next year. Doing so could inadvertently build in potential reverse causation. This could occur where innovation outcome variables are potentially measured before R&D tax credit claims (i.e. overlap between the innovation outcome years and the R&D tax credit years). To address this issue, Figure 7 highlights how these key variables are measured in our analysis, to ensure there is no potential overlap that could build in the potential for reverse causation.



Note: This is an illustrative example, which can be applied to any years in the sample period.

Figure 7: Data set up for timing of key variables

In the illustrative example shown in Figure 7, the only possible overlap comes in the years 2021. Here for a firm that indicated they had introduced a radical innovation in the 2023 survey, the earliest possible year this innovation might have occurred in 2021. Similarly, for the same firm that indicated they had claimed an R&D tax credit in the 2021 survey, the most recent year this claim could relate to is 2021. As noted above, R&D spending must pre-date any R&D tax credit claim in the vast majority of instances. Therefore, even in this extreme case, the R&D spending will always pre-date the innovation activity. Following this example, the other extreme would be a firm whose 2021 survey response indicated an R&D tax credit claim in 2019, and their 2023 survey response indicated innovation activity in 2023. This case would indicate a maximum five-year time lag between policy intervention and innovation outcome (i.e. between 2019 and 2023).

This data set up is in line with the recommendations of the Oslo Manual (OECD/Eurostat 2018) and the practice of most innovation surveys (e.g. the Community Innovation Survey/CIS, or UK Innovation Survey). The CIS uses a three-year observation period for collecting firm-level R&D and innovation data. The length of the observation period should ensure that R&D and innovation activities, from the beginning to their completion, are covered. However, the manual also notes that this time window (i.e. three years) can be inappropriate for R&D activities that require longer lead times, such as those which feed into radical innovation. Therefore, our use of a maximum 5 year lag enables sufficient time for firms to reconfigure their resources, as they seek to convert R&D expenditure into radical innovation (for further discussion of this type of time lag effect in firm-level R&D, see Kaiser & Kuhn 2012; Vanino et al. 2019; Mulligan et al. 2022; Lenihan et al 2025).

Finally, the LSBS divides survey respondents up into three cohorts for certain questions (labelled A, B and C). All firms are asked a set of ‘core’ questions, which includes innovation outcomes. However, only firms allocated to what is known as ‘Cohort C’ in each survey year are asked to respond to the question on whether they claimed an R&D tax credit. The rationale for this choice in how to conduct the survey is that firms were finding it too time-consuming to fill out, and were thus less likely to continue participating. In a given year a firm can be in one cohort only, and each year cohorts are independent of one another (e.g. a firm does not automatically stay in Cohort C in multiple years, it could be allocated to any cohort in any given year). This is a key issue for the current analysis, as we do not want to inadvertently introduce false negatives into our R&D tax credit variable (e.g. a firm in Cohort A or B may or may not have claimed an R&D tax credit in a given year, but we cannot know this based on its survey responses). Therefore, in the years we measure our R&D tax credit variable, we only use firms that appear in Cohort C in that year. We then trace these firms through to measure their innovation outcomes in subsequent years (i.e. as shown in Figure 7). In this way, we never include firms that were not specifically asked whether they claimed an R&D tax credit, and thus eliminate the potential for false negatives in the analysis.

2.5. Control variables

The LSBS captures a rich bank of firm characteristics which our analysis can use as control variables. This helps to ensure an accurate comparison of like-with-like when examining the effectiveness of R&D tax credits. Table 1 defines all variables used in the analysis. Summary statistics for these variables are provided in Table 2 for the overall sample. Table 3 sub-divides the overall sample between R&D tax credit claimants and non-claimants, as this is a crucial aspect of our analysis. Finally, Table 4 sub-divides the overall sample further, between R&D tax credit claimants and non-claimants who are located inside and outside of the Golden Triangle.

Table 1: Definition of variables used in the analysis

General innovation	Binary variable = 1 if firm introduced an incremental or radical product or process innovation; 0 otherwise.
Product innovation	Binary variable = 1 if firm introduced an incremental or radical product innovation; 0 otherwise.
Radical product innovation	Binary variable = 1 if firm introduced a radical product innovation; 0 otherwise.
Tax credit	Binary variable = 1 if firm claimed an R&D tax credit; 0 otherwise.
Golden Triangle	Binary variable = 1 if firm was located in the Local Enterprise Partnership regions of Greater Cambridge & Peterborough, London, or Oxfordshire; 0 otherwise.
Firm size	Categorical variables: Small includes firms with less than 49 employees; Medium-sized 50-249 employees; Large; greater than 249 employees
Firm size (continuous)	Average size of firm over last three years measured by number of employees.
Log firm sales	The natural logarithm of average firm sales (inflation adjusted) over the last three years.
Exports	Binary variable = 1 if firm was engaged in exporting internationally; 0 otherwise.
Intent to grow in 3 years	Binary variable = 1 if firm intends to grow their business in the next three years; 0 otherwise.
Profit	Binary variable = 1 if firm indicates they had made a profit; 0 otherwise.
Training Resources	Binary variable = 1 if firm indicates they offered any training to employees; 0 otherwise.
Financial obstacle	Binary variable = 1 if firm had difficulty in obtaining finance; 0 otherwise
Staffing and skills obstacle	Binary variable = 1 if firm found staff recruitment and skills as an obstacle to the success of business; 0 otherwise.
Market competition obstacle	Binary variable = 1 if firm found competition in the market as an obstacle to the success of business; 0 otherwise.
Legal form is Business	Binary variable = 1 if firm describes itself as a Business; 0 otherwise
Legal form is Organisation	Binary variable = 1 if firm describes itself as an Organisation; 0 otherwise.
Legal form is Proprietorship	Binary variable = 1 if firm describes itself as a Sole Proprietorship; 0 otherwise.
Obtained strategic advice	Binary variable = 1 if firm received strategic information/advice; 0 otherwise.

Obtained strategic advice from University	Binary variable = 1 if firm received strategic information/advice from University; 0 otherwise.
Turnover increased	Binary variable = 1 if firm indicates its turnover increased in the past 12 months compared to the previous 12 months; 0 otherwise.
Turnover remained the same	Binary variable = 1 if firm indicates its turnover remained the same in the past 12 months compared to the previous 12 months; 0 otherwise.
Turnover declined	Binary variable = 1 if firm indicates its turnover declined in the past 12 months compared to the previous 12 months; 0 otherwise.
Log firm age	The natural logarithm of average firm age over the last three years.
Expecting turnover growth next year	Binary variable = 1 if the firm expects any positive turnover growth for the next 12 months; 0 otherwise.
Expecting no change in turnover next year	Binary variable = 1 if the firm expects no change in turnover for the next 12 months; 0 otherwise.
Expecting decline in turnover next year	Binary variable = 1 if the firm expects decline in turnover for the next 12 months; 0 otherwise.
Family owned	Binary variable = 1 if the firm is a family-owned business or is majority-owned by members of the same family ; 0 otherwise.
Women led	Binary variable = 1 if the firm has at least one director/partner who is a woman; 0 otherwise.
Ethnic led	Binary variable = 1 if the firm has at least one director/partner who is from an ethnic minority group; 0 otherwise.
Sector (SIC 1-digit level)	Categorical variables: Primary = 0; Manufacturing = 1; Construction = 2; Wholesale/Retail = 3; Transport/Storage = 4; Accommodation/Food = 5; Information/Communication = 6; Financial/Real estate = 7; Professional/Scientific = 8; Administrative/Support = 9; Education = 10; Health/Social work = 11; Arts/Entertainment = 12; Other service = 13
Notes: The definition for Golden Triangle listed here represents the 'narrow' definition used in the main analysis, for full set of definitions used across all analyses see Section 2.1.	

Table 2: Descriptive statistics (full sample)

	Firm-year observations=25,763; Unique firms=4,551			
	Mean	SD	Min	Max
General innovation	0.41	0.49	0.00	1.00
Product innovation	0.24	0.42	0.00	1.00
Radical product innovation	0.12	0.32	0.00	1.00
Tax credit (1=yes)	0.03	0.18	0.00	1.00
Golden Triangle (1=yes)	0.13	0.34	0.00	1.00
Small (1=yes)	0.86	0.35	0.00	1.00
Medium (1=yes)	0.14	0.35	0.00	1.00
Large (1=yes)	0.00	0.06	0.00	1.00
Firm size (average of last 3 years)	21.56	39.23	0.00	583.33
Firm sales (average of last 3 years in thousands)	21.18	67.14	0.00	4838.71
Exports (1=Yes)	0.24	0.43	0.00	1.00
Intent to grow in 3 years (1=Yes)	0.72	0.45	0.00	1.00
Profit (1=Yes)	0.81	0.39	0.00	1.00
Training Resources (1=Yes)	0.16	0.36	0.00	1.00
Financial obstacle (1=Yes)	0.10	0.30	0.00	1.00
Staffing and skills obstacle(1=Yes)	0.22	0.41	0.00	1.00
Market competition obstacle (1=Yes)	0.28	0.45	0.00	1.00
Legal form is Business (1=Yes)	0.54	0.50	0.00	1.00
Legal form is Organisation (1=Yes)	0.14	0.35	0.00	1.00
Legal form is Proprietorship (1=Yes)	0.00	0.00	0.00	0.00
Obtained strategic advice from University (1=Yes)	0.00	0.06	0.00	1.00
Turnover increased (1=Yes)	0.38	0.49	0.00	1.00
Turnover remained the same (1=Yes)	0.23	0.42	0.00	1.00
Turnover declined (1=Yes)	0.37	0.48	0.00	1.00
Firm age (average of last 3 years)	19.35	15.01	0.00	78.00
Obtained strategic advice (1=Yes)	0.06	0.24	0.00	1.00
Expecting turnover growth next year (1=Yes)	0.41	0.49	0.00	1.00
Expecting no change in turnover next year (1=Yes)	0.45	0.50	0.00	1.00
Expecting decline in turnover next year (1=Yes)	0.11	0.32	0.00	1.00
Family owned (1=yes)	0.69	0.46	0.00	1.00
Women led (1=yes)	0.38	0.49	0.00	1.00
Ethnic led (1=yes)	0.04	0.19	0.00	1.00

Notes: As detailed by DBT (2023), some firms grow over the sample period to a point where they are larger than the 249-employee medium-size definition. This occurs for less than 1% of the full sample. Following the recommendation of DBT (2023), we classify this small number of firms as medium-sized for the purposes of analysis. In addition, although the empirical analysis uses the logarithms of firm sales and firm age, the summary statistics present these variables in their original units for ease of interpretation. Both points also apply to Tables 3 and 4.

Table 3: Descriptive statistics for SMEs that claim and do not claim R&D tax credits

	TC=1; n=2,745; N=462				TC=0; n=24,873; N=4550			
	Mean	SD	Min	Max	Mean	SD	Min	Max
General innovation	0.76	0.43	0.00	1.00	0.39	0.49	0.00	1.00
Product innovation	0.46	0.50	0.00	1.00	0.23	0.42	0.00	1.00
Radical product innovation	0.38	0.49	0.00	1.00	0.11	0.31	0.00	1.00
Golden Triangle (1=yes)	0.12	0.33	0.00	1.00	0.13	0.34	0.00	1.00
Small (1=yes)	0.74	0.44	0.00	1.00	0.86	0.34	0.00	1.00
Medium (1=yes)	0.25	0.43	0.00	1.00	0.13	0.34	0.00	1.00
Large (1=yes)	0.01	0.07	0.00	1.00	0.00	0.06	0.00	1.00
Firm size (average of last 3 years)	37.53	45.98	0.00	319.67	20.98	38.85	0.00	583.33
Firm sales (average of last 3 years)	59.15	188.68	0.00	4838.71	19.72	57.04	0.00	1792.11
Exports (1=Yes)	0.65	0.48	0.00	1.00	0.22	0.42	0.00	1.00
Intent to grow in 3 years (1=Yes)	0.92	0.27	0.00	1.00	0.71	0.45	0.00	1.00
Profit (1=Yes)	0.82	0.38	0.00	1.00	0.81	0.39	0.00	1.00
Training Resources (1=Yes)	0.18	0.39	0.00	1.00	0.15	0.36	0.00	1.00
Financial obstacle (1=Yes)	0.09	0.29	0.00	1.00	0.10	0.30	0.00	1.00
Staffing and skills obstacle(1=Yes)	0.26	0.44	0.00	1.00	0.22	0.41	0.00	1.00
Market competition obstacle (1=Yes)	0.31	0.46	0.00	1.00	0.28	0.45	0.00	1.00
Legal form is Business (1=Yes)	0.70	0.46	0.00	1.00	0.53	0.50	0.00	1.00
Legal form is Organisation (1=Yes)	0.03	0.17	0.00	1.00	0.14	0.35	0.00	1.00
Legal form is Proprietorship (1=Yes)	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
Obtained strategic advice from University (1=Yes)	0.01	0.11	0.00	1.00	0.00	0.06	0.00	1.00
Turnover increased (1=Yes)	0.48	0.50	0.00	1.00	0.38	0.48	0.00	1.00
Turnover remained the same (1=Yes)	0.20	0.40	0.00	1.00	0.23	0.42	0.00	1.00
Turnover declined (1=Yes)	0.32	0.47	0.00	1.00	0.37	0.48	0.00	1.00
Firm age (average of last 3 years)	19.61	14.31	2.00	74.50	19.34	15.03	0.00	78.00
Obtained strategic advice (1=Yes)	0.13	0.34	0.00	1.00	0.06	0.24	0.00	1.00
Expecting turnover growth next year (1=Yes)	0.60	0.49	0.00	1.00	0.41	0.49	0.00	1.00
Expecting no change in turnover next year (1=Yes)	0.31	0.46	0.00	1.00	0.45	0.50	0.00	1.00
Expecting decline in turnover next year (1=Yes)	0.08	0.27	0.00	1.00	0.12	0.32	0.00	1.00
Family owned (1=yes)	0.59	0.49	0.00	1.00	0.69	0.46	0.00	1.00
Women led (1=yes)	0.39	0.49	0.00	1.00	0.38	0.49	0.00	1.00
Ethnic led (1=yes)	0.04	0.19	0.00	1.00	0.04	0.19	0.00	1.00

Notes: TC=1 indicates that the firm applied for a tax credit in the last three years, n is the number of observations, and N is the number of firms

Table 4: Descriptive statistics for SMEs that claim and do not claim R&D tax credits, by location inside and outside the Golden Triangle

	TC=1								TC=0							
	GT=1; n=299; N=50				GT=0; n=2,446; N=412				GT=1; n=3,343; N=624				GT=0; n=21,530; N=3,926			
	Mean	SD	Min	Max	Mean	SD	Min	Max	Mean	SD	Min	Max	Mean	SD	Min	Max
General innovation	0.76	0.43	0.00	1.00	0.76	0.43	0.00	1.00	0.44	0.50	0.00	1.00	0.39	0.49	0.00	1.00
Product innovation	0.47	0.50	0.00	1.00	0.46	0.50	0.00	1.00	0.25	0.43	0.00	1.00	0.22	0.42	0.00	1.00
Radical product innovation	0.47	0.50	0.00	1.00	0.37	0.48	0.00	1.00	0.13	0.34	0.00	1.00	0.10	0.30	0.00	1.00
Small (1=yes)	0.85	0.36	0.00	1.00	0.73	0.44	0.00	1.00	0.84	0.37	0.00	1.00	0.87	0.34	0.00	1.00
Medium (1=yes)	0.15	0.36	0.00	1.00	0.27	0.44	0.00	1.00	0.16	0.36	0.00	1.00	0.13	0.34	0.00	1.00
Large (1=yes)	0.00	0.00	0.00	0.00	0.01	0.08	0.00	1.00	0.01	0.08	0.00	1.00	0.00	0.05	0.00	1.00
Firm size (average of last 3 years)	27.53	39.25	0.00	220.00	38.93	46.70	0.00	319.67	24.44	45.92	0.00	490.00	20.45	37.60	0.00	583.33
Firm sales (average of last 3 years)	93.42	479.70	0.00	4838.71	54.53	97.29	0.00	838.73	25.98	72.40	0.00	1000.00	18.72	54.14	0.00	1792.11
Exports (1=Yes)	0.72	0.45	0.00	1.00	0.64	0.48	0.00	1.00	0.32	0.47	0.00	1.00	0.21	0.41	0.00	1.00
Intent to grow in 3 years (1=Yes)	0.91	0.29	0.00	1.00	0.92	0.27	0.00	1.00	0.75	0.44	0.00	1.00	0.70	0.46	0.00	1.00
Profit (1=Yes)	0.71	0.46	0.00	1.00	0.84	0.37	0.00	1.00	0.79	0.41	0.00	1.00	0.81	0.39	0.00	1.00
Training Resources (1=Yes)	0.18	0.39	0.00	1.00	0.18	0.38	0.00	1.00	0.15	0.36	0.00	1.00	0.16	0.36	0.00	1.00
Financial obstacle (1=Yes)	0.12	0.33	0.00	1.00	0.09	0.28	0.00	1.00	0.11	0.31	0.00	1.00	0.10	0.30	0.00	1.00
Staffing and skills obstacle(1=Yes)	0.26	0.44	0.00	1.00	0.26	0.44	0.00	1.00	0.24	0.43	0.00	1.00	0.21	0.41	0.00	1.00
Market competition obstacle (1=Yes)	0.28	0.45	0.00	1.00	0.31	0.46	0.00	1.00	0.30	0.46	0.00	1.00	0.28	0.45	0.00	1.00
Legal form is Business (1=Yes)	0.64	0.48	0.00	1.00	0.70	0.46	0.00	1.00	0.54	0.50	0.00	1.00	0.53	0.50	0.00	1.00
Legal form is Organisation (1=Yes)	0.02	0.13	0.00	1.00	0.03	0.18	0.00	1.00	0.15	0.35	0.00	1.00	0.14	0.35	0.00	1.00
Legal form is Proprietorship (1=Yes)	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
Obtained strategic University (1=Yes)	0.00	0.00	0.00	0.00	0.01	0.11	0.00	1.00	0.00	0.05	0.00	1.00	0.00	0.06	0.00	1.00
Turnover increased (1=Yes)	0.49	0.50	0.00	1.00	0.48	0.50	0.00	1.00	0.39	0.49	0.00	1.00	0.37	0.48	0.00	1.00
Turnover remained the same (1=Yes)	0.13	0.34	0.00	1.00	0.21	0.41	0.00	1.00	0.25	0.43	0.00	1.00	0.23	0.42	0.00	1.00
Turnover declined (1=Yes)	0.38	0.49	0.00	1.00	0.31	0.46	0.00	1.00	0.35	0.48	0.00	1.00	0.38	0.48	0.00	1.00
Firm age (average of last 3 years)	17.88	13.48	2.00	58.50	19.85	14.41	2.00	74.50	19.29	15.41	0.00	76.00	19.35	14.97	0.00	78.00
Obtained strategic advice (1=Yes)	0.14	0.35	0.00	1.00	0.13	0.34	0.00	1.00	0.08	0.28	0.00	1.00	0.06	0.23	0.00	1.00
Expect turnover growth next year (1=Yes)	0.56	0.50	0.00	1.00	0.60	0.49	0.00	1.00	0.44	0.50	0.00	1.00	0.40	0.49	0.00	1.00
Expect no change in turnover (1=Yes)	0.35	0.48	0.00	1.00	0.30	0.46	0.00	1.00	0.42	0.49	0.00	1.00	0.46	0.50	0.00	1.00
Expect decline in turnover (1=Yes)	0.08	0.28	0.00	1.00	0.08	0.27	0.00	1.00	0.12	0.32	0.00	1.00	0.11	0.32	0.00	1.00
Family owned (1=yes)	0.40	0.49	0.00	1.00	0.61	0.49	0.00	1.00	0.64	0.48	0.00	1.00	0.70	0.46	0.00	1.00
Women led (1=yes)	0.27	0.44	0.00	1.00	0.40	0.49	0.00	1.00	0.35	0.48	0.00	1.00	0.38	0.49	0.00	1.00
Ethnic led (1=yes)	0.10	0.30	0.00	1.00	0.04	0.20	0.00	1.00	0.09	0.29	0.00	1.00	0.03	0.17	0.00	1.00

Notes: TC=1 indicates that the firm applied for a tax credit in the last three years, GT=1 indicates the firm is located in the golden triangle (narrow); n is the number of observations, and N is the number of firms

3. Methodology

To ensure a robust analysis, we implement a two-step econometric process that aims to isolate the impact of R&D tax credits for SMEs inside and outside of the Golden Triangle. To achieve this, our econometric analysis combines Propensity Score Matching (PSM) as a first step, with a Difference-in-Differences (DiD) estimator as a second step. Henceforth this methodology is referred to as PSM-DiD. The initial PSM ensures that SMEs which claim R&D tax credits are matched with an appropriate control group based on observable business characteristics. The subsequent DiD accounts for possible omitted variables which may nevertheless influence SMEs' innovation outcomes.

3.1. Step one: Propensity Score Matching

For step one, it is important to highlight that evaluating whether R&D tax credits drive firm-level innovation necessitates considering the well-known 'selection into treatment' problem that is common to all types of public R&D support for firms (see e.g. Czarnitzki et al. 2011; Labeaga et al. 2021; Lenihan et al. 2024). In the abstract, an evaluation of like-with-like would compare the innovation activities of firms that claimed R&D tax credits, with the counterfactual scenario where the same firms did not claim this support. Observing this scenario is obviously not possible, so the counterfactual needs to be estimated.

This can be achieved based on the data of firms that do not claim an R&D tax credit but are similar to those that do claim. The commonly used terminology in this type of study dubs R&D support recipients as 'treated' firms, while the firms that do not received R&D tax credits are called 'untreated' or control firms. We construct the counterfactual of untreated firms, that have the same pre-treatment probability of claiming R&D tax credits as treated firms. We do this based on a set of observable firm characteristics, through PSM. PSM is commonly used as a reliable approach to address research questions such as ours (see e.g. Czarnitzki & Lopes-Bento 2013; Vanino et al. 2019; Mulligan 2024).

The key underpinning feature of our analysis is potential location specific effects which may enable firms to leverage additional innovation benefits from R&D tax credits.

Therefore, in the first step of our modelling, we estimate firms' likelihood to be located within the Golden Triangle, as shown in Equation (1):

$$GT_i = \alpha + \beta_x X_i' + u_i \quad (1)$$

Before discussing Equation (1), it is important to note that in matching on SMEs likelihood of being located in a specific region is common practice in the regional studies/regional science literature (see e.g. Clifford et al. 2025; Fantechi & Fratesi 2024a; 2024b; 2023a). However, it deviates from the norm in the innovation studies literature, which typically matches on firms' propensity to receive the public R&D funding in an effort to overcome the selection into treatment problem. While our main focus is on the Golden Triangle, we cannot ignore this issue. Therefore, as detailed in Section 3.3 below, we perform a series of robustness tests that directly account for this and other potential issues.

Returning to Equation (1), $GT_i = 1$ if firm i is located in the Golden Triangle (narrow definition; see Section 2.1), and 0 otherwise. X_i' is a vector of control variables, as detailed in Section 2.5. In a PSM analysis, it is very important to include as many relevant variables as possible, to ensure a fair match of like-with-like. In addition to matching on these variables, our PSM analysis applies a common support condition to ensure that there is sufficient overlap in terms of propensity score between treated firms and the matched control group (Leuven & Sianesi 2018). To avoid so-called 'bad matches', we employ a caliper threshold which sets a tolerance level on the maximum propensity score distance between treated and untreated firms. The caliper option is set to 0.25 times the standard deviation of the propensity scores (Guerzoni & Raiteri, 2015). Treated firms that can be matched to untreated firms within this caliper range are termed 'on support' and are included in the analysis. However, treated firms that cannot be matched are termed 'off support' and are excluded from the analysis. In addition, treated firms are constrained to an exact match based on the year a firm claimed an R&D tax credit.

Caliendo and Kopeinig (2008), in their study on the implementation of PSM models, highlight that the choice of the matching algorithm to apply is a matter of a trade-off in terms of bias and efficiency of the matching estimator. However, given that PSM is most frequently applied with secondary (i.e. non-experimental) datasets, this key choice fundamentally relies on the nature of the data used in the study (Leuven & Sianesi 2018). For nearest-neighbour matching, using only the closest observation in terms of propensity score as a comparison for treated firms, allows for smaller bias at the price of higher variance (Almus & Czarnitzki 2003; Czarnitzki et al. 2011; Czarnitzki & Lopes-Bento 2013). However, the control group used in our analysis is much larger than the treated group. In instances such as this, Guerzoni and Raiteri (2015) recommend using up to three neighbours to build the counterfactual outcomes in order to raise efficiency. While this kind of oversampling allows us to gain efficiency, the caliper threshold and common support condition ensures that using more information does not lead to bad matches (Guerzoni & Raiteri 2015). Finally, to ensure a fair match of like-with-like has occurred, we perform a series of diagnostic tests developed by Leuven and Sianesi (2018) to test the quality of the balance between control group and treated firms. These tests reveal that the samples to be considered sufficiently balanced, indicating that the results of the matching process are robust (see Section 4.1).

3.2. Step two: Difference in Differences

Having discussed how we build a balanced sample suitable for the analysis, we now turn to step two which estimates the effectiveness of R&D tax credits for SMEs within this sample. One limitation of the PSM approach is that it relies on the so-called Conditional Independence Assumption (CIA). According to the CIA, treatment and outcome are assumed to be statistically independent for firms with the same set of observable characteristics (Rubin 2077). This is a very strict assumption, implying that any differences in innovation outcomes between treated and control groups post-treatment can be attributed to the treatment alone. However, PSM can only control for observed variables. Therefore, our second step performs a DiD regression analysis to control for unobservable pre-treatment trends. The second step consists of estimating the following innovation production function in Equation (2), using our matched sample:

$$Innovation_{ist}^{k}(1 = Yes) = \alpha + \beta_x X_{it-3}' + \beta_{innov_{lag}} Innovation_{its-3}^{k}(1 = Yes) + \\ \beta_{TC} TC_{it-2} + \beta_{GT} GT_i + \beta_{TC,GT} TC_{it-2} \times GT_i + \beta_{\overline{x}} \overline{X_i'} + \theta_s + \zeta_t + u_{ist} \quad (2)$$

The left-hand side of Equation (2) represents the outcome variable of interest in our study, $Innovation_{ist}^{k}(1 = Yes)$ which is an indicator of firm innovation activity. This binary variable takes the value 1 if firm i, belonging to sector s, engaged in k type innovation between periods t and $t+3$ and 0, otherwise. The k type innovation can encompass either general innovation, product innovation, or radical product innovation. In the right-hand side (RHS) of Equation (2), α is a constant, β terms are the parameters to be estimated, and u_{ist} is the error term. $X_{it-3}{}'$ is a vector of control variables. The control variables are lagged $(t-3\ to\ t)$ relative to the innovation outcome variable window $(t\ to\ t+3)$. Such a lagged structure helps to mitigate concerns regarding reverse causality, ensuring that the control variables are determined prior to the submission of an R&D tax credit claim and any realised innovation outcomes.

We include the control variables to capture any remaining imbalance following the matching process. We also account for the lagged innovation outcome variable $(Innovation_{its-3}^{k}(1=Yes))$ in the RHS of Equation (2) to further alleviate concerns on endogeneity. θ_s and ζ_t denote sector and time dummies. These control for time-invariant, sector-specific characteristics (such as the regulatory environment that is sector-specific) and common macro time-varying factors (such as business cycle fluctuations) that influence firms' innovation outcomes. $\overline{X_i'}$ are firm-level means of time-varying covariates known as 'Mundlak terms' which account for correlated random effects (see more below).

TC_{it-2} represents whether firm i claimed R&D tax credit between periods $t-2$ to t, while GT_i represents whether firm i was located in the Golden Triangle. Importantly, $TC_{it-2} \times GT_i$ is an interaction term, measuring whether firm i that was located in the Golden Triangle also claimed an R&D tax credit between periods $t-2$ to t. The key coefficient of interest is $\beta_{TC,GT}$, which indicates whether the R&D tax credit drives future innovation outputs. The coefficient is interpreted relative to the coefficient β_{TC}, which indicates the impact of R&D tax credits for firms in non-Golden Triangle regions.

We estimate Equation (2) using a probit regression model (for binary measures of innovation). As such, marginal effects of the interaction terms are calculated as the difference of the marginal effects between firms that claimed an R&D tax credit and were located in the Golden Triangle, and other treated firms that were located in the UK's other regions. That is; by holding all other control variables constant, we calculate the discrete change of the average marginal effects of treated firms, depending on firm location. This is important because the marginal effects of interaction terms in non-linear models can be influenced by all other control variables in the model.

One final key point for our second step analysis is that we use correlated random effects (CRE), as opposed to the standard fixed effects, which are typically used in PSM-DiD two-step models. We use CRE because this approach provides a robust methodology for the consistent evaluation of time-invariant factors, such as firms' regional location. CRE functions as a unifying fixed and random effects scheme (Wooldridge 2010) and is often implemented through the within-between random effect (REWB) formulation (Kosfeld & Mitze 2023; Bontempi et al. 2024). A central advantage of employing the CRE method stems from the limitations of standard fixed-effects (FE) estimation. Standard FE estimation eliminates time-invariant variables, such as regional location (Kosfeld & Mitze 2023). In contrast, the random effects specification utilised by CRE ensures that the impacts of time-invariant variables are still identifiable (Kosfeld & Mitze 2023). The principal function of the CRE method is to achieve consistent estimation in panel data by mitigating potential heterogeneity bias (Kosfeld & Mitze 2023). This is achieved by introducing individual heterogeneity explicitly into the model, often through the so-called Mundlak (1978) variant, which specifies that the unobserved effects ($\overline{X_i'}$ in Equation (2)) depend on the regional means of the observable variables (Wooldridge 2010; Kosfeld & Mitze 2023). This specification is crucial for controlling for endogeneity stemming from the omission of stable, time-invariant drivers of innovation (Bontempi et al. 2024).

3.3. Robustness tests

To ensure the reliability of the findings based on our main methodological approach discussed above, we perform five key robustness tests using alternative modelling choices. Here, we briefly summarise these robustness tests, and our rationale for implementing them:

1. <u>Use several different specifications for Golden Triangle definition:</u>
   As discussed in Section 2.1, there is no single 'official' definition of the Golden Triangle. To ensure our results are not mainly driven by small changes in this key definition, we run four versions of our main model using increasingly 'broad' definitions of the Golden Triangle.

2. Run Stage 2 DiD on full sample with no matching:
   This robustness test enables us to check whether our results are driven by specifics of the stage one PSM, as well as making use of all information in our full large-scale pre-matching dataset.

3. Run Stage 1 matching with R&D tax credit as dependent variable (no matching on Golden Triangle location):
   When evaluating the impact of government R&D support on firm-level innovation, the most common approach is to create a matched sample of treated and untreated firms to enable a fair comparison of like-with-like. In our analysis, the key issue we focus on is location specific effects in the Golden Triangle. As such, our main results are based on a matched sample of firms with and equal likelihood of being located in this region. However, as discussed in Section 3.1, this leaves our main results potentially vulnerable to endogeneity caused by selection into treatment. Therefore, we re-run our main analysis following the classic matching approach with the R&D tax credit as the stage one dependent variable.

4. 3-stage process
   Similar to point 3 above, we implemented a 3-stage process with two sets of matching: Stage 1 matching dependent variable as Golden Triangle location. Stage 2 matching again with dependent variable as R&D tax credit (on the already matched stage-one sample). Stage 3 standard DiD. This helps ensure our matched sample is not biased by selection into treatment for R&D tax credit claims, or Golden Triangle location. To ensure our results are not driven by which matching step we take first, we also reverse the order of Steps 1 and 2.

5. Sensitivity of analysis to various different matching specifications
   Our main stage two model is estimated using the stage one results from a 1:3 PSM model (i.e. each treated firm is matched with three untreated nearest neighbours). To test the sensitivity of our results to changes in PSM model, we also estimate our stage one models using 1:1 and Kernel density matching approaches. We then use the results from these alternative PSM models in stage two. This enables us to test

the robustness of our stage two findings to changes in the way our propensity scores are generated.

The above robustness tests enable us to ensure that our main results are not sensitive to relatively small and reasonable changes in the modelling approach.

4. Results and discussion

This section presents and discusses the results of our main analysis. We first examine the matching procedure by which we construct a fair comparison of like-with-like, when evaluating the impact of R&D tax credits on the radical innovation performance of SMEs. We then examine how this impact unfolds in our sample of matched SMEs who claim R&D tax credits located inside and outside of the Golden Triangle.

4.1. Stage one: Constructing a matched sample

To apply the PSM-DiD analysis discussed in Section 3, we first need to predict SMEs' probability of being located in the Golden Triangle. To achieve this, we estimate a probit model that controls for SME characteristics which may determine selection into treatment. The purpose of this is to create a matched sample of SMEs where the only difference between treatment and control groups after matching is location inside or outside the Golden Triangle. This matching procedure is applied year by year, using the covariates observed in the firm's first year of appearance in the sample to determine the match. The probit model results for a representative year (2021) are shown in Table 5.

Table 5: Probit model estimating SMEs' probability location in the Golden Triangle

Variables	Coefficients	Standard Errors
Small (1=yes)	-0.298	(0.201)
Medium (1=yes)	-0.297	(0.184)
Family owned (1=Yes)	-0.00116	(0.0194)
Women led (1=Yes)	-0.0518***	(0.0167)
Ethnic led (1=Yes)	0.149***	(0.0349)
Firm size (average of last 3 years)	-0.00127**	(0.000621)
Log firm sales (average of last 3 years)	0.0227***	(0.00662)
Exports (1=Yes)	0.0394**	(0.0196)
Intent to grow in 3 years (1=Yes)	-0.0163	(0.0199)
Profit (1=Yes)	-0.0225	(0.0196)
Financial obstacle (1=Yes)	0.0125	(0.0411)
Staffing and skills obstacle(1=Yes)	0.0143	(0.0248)
Market competition obstacle (1=Yes)	0.0302	(0.0236)
Obtained strategic advice (1=Yes)	0.0331	(0.0327)
Legal form is Business (1=Yes)	0.0627*	(0.0368)
Legal form is Organisation (1=Yes)	0.0631	(0.0390)
Turnover increased (1=Yes)	0.895***	(0.0681)
Turnover remained the same (1=Yes)	0.925***	(0.0680)
Turnover declined (1=Yes)	0.877***	(0.0685)
Expecting turnover growth next year (1=Yes)	-0.118*	(0.0690)
Expecting no change in turnover next year (1=Yes)	-0.117*	(0.0693)
Expecting decline in turnover next year (1=Yes)	-0.148**	(0.0737)
Sector (SIC 1-digit level, 1=Manufacturing)	-0.0133	(0.0307)
Sector (SIC 1-digit level, 1=Construction)	0.0587	(0.0359)
Sector (SIC 1-digit level, 1=Wholesale/Retail)	0.0157	(0.0304)
Sector (SIC 1-digit level, 1=Transport/Storage)	0.00313	(0.0428)
Sector (SIC 1-digit level, 1=Accommodation/Food)	0.101**	(0.0500)
Sector (SIC 1-digit level, 1=Information/Communication)	0.135***	(0.0441)
Sector (SIC 1-digit level, 1=Financial/Real estate)	0.254***	(0.0530)
Sector (SIC 1-digit level, 1=Professional/Scientific)	0.111***	(0.0333)
Sector (SIC 1-digit level, 1=Administrative/Support)	0.112***	(0.0423)
Sector (SIC 1-digit level, 1=Education)	0.152**	(0.0627)
Sector (SIC 1-digit level, 1=Health/Social work)	0.110**	(0.0500)
Sector (SIC 1-digit level, 1=Arts/Entertainment)	0.0871	(0.0643)
Sector (SIC 1-digit level, 1=Other service)	0.197***	(0.0634)
Log firm age (average of last 3 years)	0.0228*	(0.0122)
Observations	1,912	
Log likelihood	723.3	
Pseudo R^2	0.0794	

Notes: * p < 0.1; ** p < 0.05; *** p < 0.01. Robust standard errors in parentheses.

For the matching procedure to be satisfactory, it requires that the mean values of the treatment and control groups do not differ significantly from the pre-treatment variables after matching. Table 6 displays the results of a balance test of the covariates employed in the estimation of the propensity score. Here, a t-test is performed to test whether the mean value of each variable is the same in the treatment group and the control group after matching. The results show that there is no significant difference between the observable characteristics of the treated firms and untreated control group after matching. Table 6 also presents a series of diagnostic tests developed by Leuven and Sianesi (2018) to test the quality of the balance between control group and treated firms. These tests reveal that the Rubin's B score, capturing the absolute standardised difference of means of a linear index of the propensity score in treated and matched non-treated groups, is below the 25 per cent maximum threshold. Similarly, the Rubin's R score, which shows the ratio of treated to matched non-treated variances of the propensity score index, is within the required range of 0.5 and 2 for the samples to be considered sufficiently balanced. Similarly, the mean bias falls below the five per cent threshold after the matching. Our analysis satisfies all matching criteria as specified by Leuven and Sianesi (2018), indicating that the results of the matching process are robust.

Table 6: Balance of the control variables after matching treated and untreated firms

	Mean		Bias	t-test	
	Treated	Control	%	t-value	p-value
Small (1=yes)	0.919	0.916	.9	0.100	0.917
Medium (1=yes)	0.078	0.078	0	0.000	1.000
Family owned (1=Yes)	0.707	0.726	-4.2	-0.480	0.634
Women led (1=Yes)	0.344	0.326	3.8	0.460	0.649
Ethnic led (1=Yes)	0.067	0.062	2.2	0.230	0.815
Firm size (average of last 3 years)	15.317	14.903	1.2	0.160	0.876
Log firm sales (average of last 3 years)	1.263	1.192	3.7	0.430	0.664
Exports (1=Yes)	0.281	0.275	1.4	0.160	0.873
Intent to grow in 3 years (1=Yes)	0.748	0.732	3.7	0.420	0.671
Profit (1=Yes)	0.763	0.758	1.2	0.130	0.893
Financial obstacle (1=Yes)	0.052	0.067	-7.2	-0.730	0.467
Staffing and skills obstacle(1=Yes)	0.174	0.172	.7	0.080	0.940
Market competition obstacle (1=Yes)	0.170	0.190	-5.5	-0.600	0.551
Obtained strategic advice (1=Yes)	0.070	0.068	1	0.110	0.910
Legal form is Business (1=Yes)	0.756	0.728	6.2	0.720	0.472
Legal form is Organisation (1=Yes)	.2	0.217	-4.3	-0.490	0.622
Turnover increased (1=Yes)	0.463	0.452	2.2	0.260	0.796
Turnover remained the same (1=Yes)	0.333	0.358	-5.4	-0.600	0.547
Turnover declined (1=Yes)	0.204	0.190	3.3	0.400	0.692
Expecting turnover growth next year (1=Yes)	0.478	0.453	4.9	0.570	0.566
Expecting no change in turnover next year (1=Yes)	0.419	0.421	-0.5	-0.060	0.954
Expecting decline in turnover next year (1=Yes)	0.085	0.109	-8.1	-0.920	0.358
Sector (1=Manufacturing)	0.052	0.052	0	0.000	1.000
Sector (1=Construction)	0.081	0.086	-1.7	-0.210	0.836
Sector (1=Wholesale/Retail)	0.107	0.089	5.5	0.720	0.470
Sector (1=Transport/Storage)	0.015	0.019	-2.4	-0.340	0.737
Sector (1=Accommodation/Food)	0.048	0.056	-3.4	-0.390	0.699
Sector (1=Information/Communication)	0.096	0.107	-4.1	-0.430	0.670
Sector (1=Financial/Real estate)	0.096	0.079	6.7	0.710	0.479
Sector (1=Professional/Scientific)	0.222	0.227	-1.2	-0.140	0.891
Sector (1=Administrative/Support)	0.081	0.088	-2.3	-0.260	0.797
Sector (1=Education)	0.041	0.046	-2.7	-0.280	0.778
Sector (1=Health/Social work)	0.059	0.058	.5	0.060	0.951
Sector (1=Arts/Entertainment)	0.022	0.016	4.3	0.520	0.601
Sector (1=Other service)	0.059	0.059	0	0.000	1.000
Log firm age (average of last 3 years)	3.096	3.095	.1	0.010	0.989
Pseudo R^2	0.008				
LR-chi^2	6.34				
p>chi^2	0.999				
MeanBias	2.9				
MedBias	2.4				
Rubin's B	21.7				
Rubin's R	0.79				

4.2. Stage two: Difference-in-Difference analysis

Our DiD analysis on the matched sample is presented in Table 7. The first row of Table 7 examines the influence of being located in the Golden Triangle (narrow definition, see Section 3.1) on SMEs radical innovation performance. Model (1) shows the most parsimonious model, while Model (6) controls for a range of potentially important factors which may influence our findings. All models in between gradually add more controls, in an effort to ensure that the results are robust and not driven by pre-existing firm, sector and time-specific differences between the SMEs. As can be seen in Table 1, the Golden Triangle location is only significant in Model (1). This suggests that the simple fact of being located in the Golden Triangle is not sufficient in and of itself to provide SMEs with an innovation premium over SMEs located in other regions. This result is somewhat surprising, given that previous research suggests there are unique proximity-based knowledge spillovers available to firms located in the Golden Triangle (Mueller et al. 2012; Helmers & Rogers 2015; Jelfs & Lawton Smith 2021; Stanfield et al. 2022).

The type of science-based and R&D-intensive knowledge spillovers produced by this type of regional agglomeration should be particularly beneficial for firms engaging in more radical forms of innovation, which usually require a greater level of R&D input and specific tacit knowledge (Hewitt-Dundas et al. 2019; Beck et al. 2016; Becker et al. 2023). On this basis, it would be reasonable to assume that, at least on average, Golden Triangle SMEs may outperform their non-Golden Triangle competitors in terms of radical innovation. However, our results suggest that this is not the case, and there is no significant difference in overall SME radical innovation performance based on whether the SMEs are located in the Golden Triangle or elsewhere. This result is potentially important for policy, as it is often assumed *a priori* that firms located in the Golden Triangle have many location-specific advantages that can help with innovation performance over firms in other UK regions (Perry 2007; Kempton et al. 2021; Martin et al. 2022; Gray & Broadhurst 2023). At least in the parameters of what the current analysis examines, our results suggest the explanatory power of this assumption may be over-stated.

Turning next to the second row of Table 7, we see the impact of R&D tax credits on SME radical innovation performance on average in the UK (i.e. not accounting for Golden Triangle location). This row highlights that R&D tax credits are highly effective at driving additional radical innovation in SMEs, relative to a matched sample of SMEs that did not submit R&D tax credit claims. These results confirm those presented in several recent studies examining the UK context, using different methodologies and data set-ups (Dechezleprêtre et al. 2023; Pless 2025; Liu et al. 2025; Lee & Lambeck 2025). This consistency lends credence to our findings and further reinforces the effectiveness of R&D tax credits in the UK context.

Moreover, it is worth noting the R&D tax credits are sometimes criticised on two accounts:

1) They mainly favour large incumbent firms with established R&D capabilities and administrative functions (Hall & Van Reenan 2000; Czarnitzki et al. 2021; Petrin & Radičić 2023).
2) They mainly favour more near-to-market, low-risk, incremental types of innovation, where the market failure rationale for government R&D support is usually weakest (Labeaga et al. 2021; Dimos et al. 2022; Lenihan et al. 2024).

Indeed, a recent study based on firms in the United States found no evidence that R&D tax credits drove additional patenting, or increased the scientific quality of patents (Melnik & Smyth 2024). Our results contrast significantly with these potential criticisms, as we find that not only are R&D tax credits highly effective at driving innovation in SMEs, but also that the impacts occur for radical innovation. As such, R&D tax credits appear to be effective at reaching a key group within the industrial base (i.e. SMEs), and a hard-to-reach policy target in terms of radical innovation.

Table 7: Results using narrow definition for the Golden Triangle

Innovation outcome: Radical product Innovation	Model 1	Model 2	Model 3	Model 4	Model 5	Model 6
Golden Triangle (GT)	0.0199**	0.00612	0.00134	0.00139	0.00109	0.000209
	(0.00930)	(0.0126)	(0.0135)	(0.0138)	(0.0138)	(0.0139)
R&D tax credit (TC)	0.0381***	0.0349**	0.0668***	0.0722***	0.0704***	0.0654***
	(0.0147)	(0.0142)	(0.0159)	(0.0165)	(0.0163)	(0.0163)
GT × TC	0.00727	0.0161	0.0305	0.0324	0.0313	0.0291
	(0.0251)	(0.0306)	(0.0430)	(0.0429)	(0.0431)	(0.0420)
Obs	8283	8283	5784	5784	5784	5784
TC obs	360	360	324	324	324	324
GT obs	2101	2101	1396	1396	1396	1396
Non GT obs	6182	6182	4388	4388	4388	4388
GT-TC firms	40	40	38	38	38	38
CRE		X	X	X	X	X
Controls			X	X	X	X
Lag DV				X	X	X
Year dummies					X	X
Sector dummies						X

Finally, in the third row Table 7 shows the impact of R&D tax credits on radical innovation for SMEs located inside the Golden Triangle, relative to R&D tax credit recipients located in the UK's other regions. Our results here show that there is no statistically significant difference in the effectiveness of the R&D tax credit for SMEs owing to their regional location, when using the narrowest possible definition of the Golden Triangle. However, Table 8 builds on these results, showing that when two slightly broader definitions of the Golden Triangle are used (i.e. Broad 1 and Broad 2 defined in Section 2.1), the results conform more to what previous academic research and policy reports suggested may be the case. The final row in Table 8 shows SMEs in these regions derived a significant additional radical innovation premium from their R&D tax credits, over and above the positive benefit achieved by SMEs in other UK regions. The final column of Table 8 highlights that this effect wears off as the definition for the Golden Triangle becomes too broad, as may be expected given the nature of proximity-based knowledge spillovers.

Table 8: Results using broad definitions of the Golden Triangle

Innovation outcome: Radical product Innovation	Broad (1)	Broad (2)	Broad (3)
Golden Triangle (GT)	-0.00128	-0.00620	-0.0123
	(0.0116)	(0.0103)	(0.00980)
R&D tax credit (TC)	0.0532***	0.0383***	0.0533***
	(0.0151)	(0.0137)	(0.0129)
GT × TC	0.0607*	0.0681**	0.0301
	(0.0342)	(0.0282)	(0.0266)
Obs	7425	8623	9220
TC obs	388	427	471
GT obs	2030	2741	3247
Non GT obs	5395	5882	5973
GT-TC firms	64	84	95
CRE	X	X	X
Controls	X	X	X
Lag DV	X	X	X
Year dummies	X	X	X
Sector dummies	X	X	X

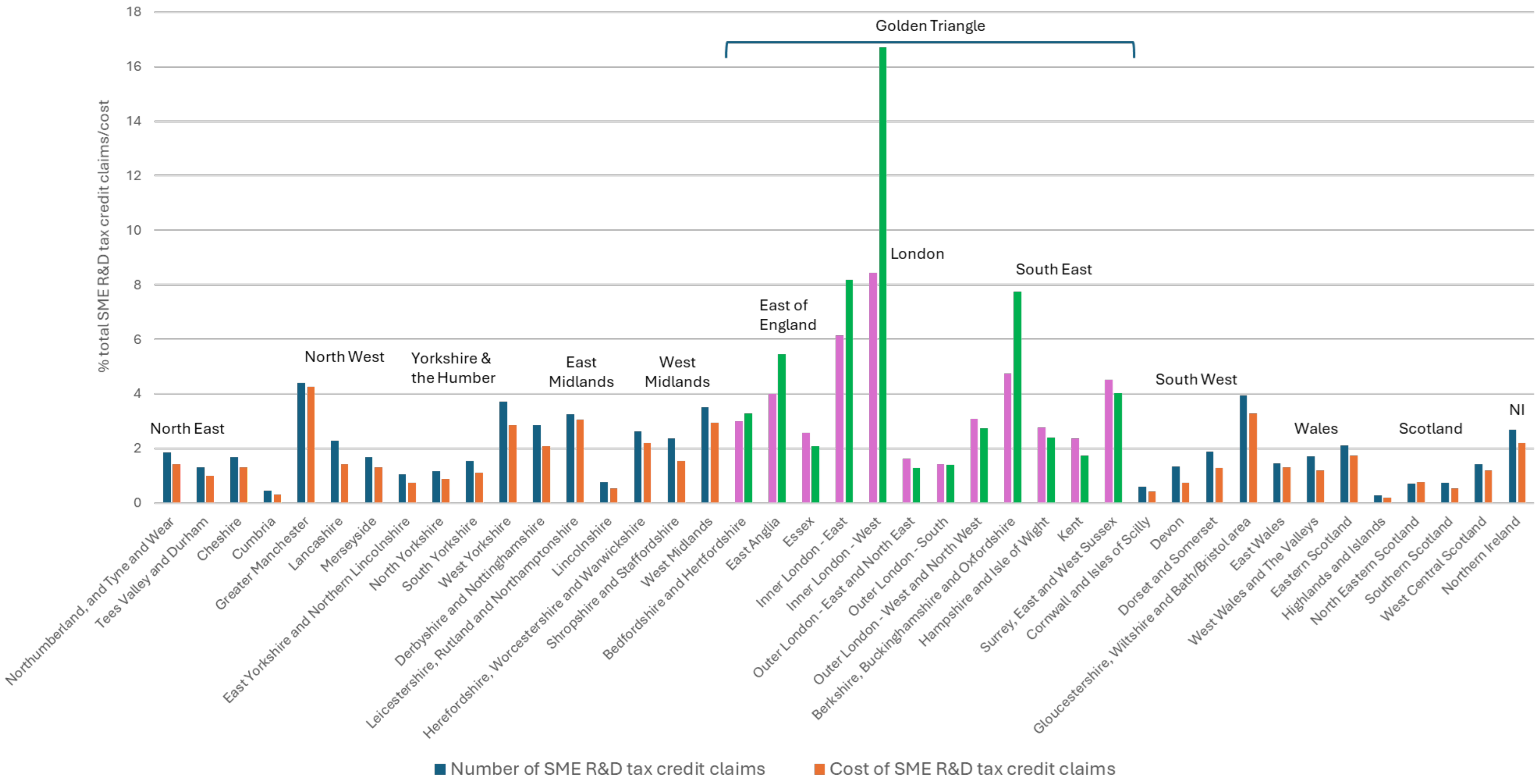
Overall, these results tally with the *a priori* assumption discussed above that Golden Triangle SMEs may be able to leverage unique proximity-based knowledge spillovers to achieve superior innovation performance with R&D tax credits. In addition, this links in well with recent studies that have highlighted that firms in regions characterised by factors such as above-average R&D and innovation intensities can derive significant additional impacts from different types of government R&D support (Alecke et al. 2021; Barzotto et al. 2019; Vanino et al. 2019; Mulligan 2024). However, none of these previous studies have specifically examined R&D tax credits. R&D tax credits function according to a distinct mechanism, where they are one-size-fits-all, aspatial, and neutral in terms of allocation (i.e. unlike R&D grants which are awarded on the basis of application criteria, any firm can claim R&D tax relief as long as they are conducting R&D). Our findings here thus add important additional information to the evidence base on how public R&D funding supports SME innovation. This new evidence is timely, given R&D tax credits are by far the largest R&D policy instrument used to help support firms' innovation in the UK.

5. Conclusions and actionable insights for policy

The objective of this research report was to examine the impact of R&D tax credits on the innovation performance of SMEs located within the UK's so-called Golden Triangle (between Oxford, Cambridge and London), versus SMEs located in the UK's other regions. The rationale for this focus was based on the fact that the Golden Triangle has received a disproportionately large share of public R&D investment over a prolonged time period. This public investment, at least in part, has helped to build a critical mass of R&D infrastructure such as Universities, science labs and clusters of high-tech firms. These amenities are largely unavailable to firms beyond the Golden Triangle. SMEs based in the Golden Triangle may be able to combine these unique location-specific advantages with the support provided through R&D tax credits to achieve superior innovation performance (relative to firms located elsewhere). This is a key concern for policymakers, as the UK R&D tax credit is by far the largest type of government R&D support for firms (circa £7 billion per year). As a one-size-fits-all, aspatial R&D support, the R&D tax credit could thus inadvertently contribute to widening regional inequality in terms of business expenditure on R&D.

Results from our analysis suggest that the UK R&D tax credit programme is highly effective at driving SME radical innovation performance. This is a significant positive benefit for SMEs located throughout the UK. However, SMEs located in the Golden Triangle do derive a substantial innovation premium from claiming R&D tax credits, over and above SMEs located in other regions. Taken in and of itself, this result highlights that the R&D tax credit programme plays an important role in supporting private firms within the UK's overall research and innovation system. In terms of providing actionable insights for policymakers, these results strengthen the case for UK innovation strategies that favour clustering and agglomeration, and the relatively recent move to place-based R&D policy (see e.g. SQW 2022).In addition, our results suggest that SMEs located outside of the Golden Triangle may require specific tailored policy interventions which enable them to leverage local advantages, as well as compensating for certain key factors which are unavailable in their local context.

In addition to achieve a holistic understanding of these findings, it is important to consider them within the context of overall business R&D investment trends in the UK. To achieve this, it is useful to examine our results alongside Figure 8. This Figure highlights the total number of R&D tax credit claims submitted by SMEs in 2023, as well as the amount of these claims (for scale, presented as a percentage of the total), sub-divided by NUTS1 and NUTS2 UK regions. Data for the Golden Triangle (broadly defined by NUTS1 regions) is presented in pink and green, to differentiate it from the rest of the UK.



Source: HMRC Research and Development Tax Credits Statistics 2023

Figure 8: SME R&D tax credit claims and cost by NUTS1 and NUTS2 region

Figure 8 shows that the three NUTS1 Golden Triangle regions lead the rest of the UK by a considerable margin, both in terms of SMEs submitting R&D tax credit claims, and the level of these claims. Approximately 47% of total R&D tax credit claims were made by SMEs in the Golden Triangle, while approximately 56% of the total cost of SME R&D tax credit claims occurred in the Golden Triangle. In the context of this report's findings, Figure 8 bears out two important points:

- There are significantly more R&D-active SMEs in the Golden Triangle capable of submitting R&D tax credit claims, relative to the rest of the UK.
- SMEs in the Golden Triangle are able to submit much larger R&D tax credit claims, because they have larger overall R&D capabilities.

These points draw out a crucial nuance to our overall findings. While R&D tax credits are highly effective across the UK, they are more effective in the Golden Triangle. Therefore, Golden Triangle regions may be able to achieve a double benefit from R&D tax credits on aggregate. This may be because the Golden Triangle has several region-specific features that enables firms located there to leverage the impacts of R&D tax credits. Moreover, these same Golden Triangle firms can leverage these positive benefits to a greater extent, given their larger overall R&D investment profiles. This is an important point when considering the role of different R&D supports for firms in the UK, and how best to achieve place-based R&D policy goals.

Figure 8 draws this point out further, by also examining R&D tax credit claims at NUTS2 level. Even at this level more granular, Figure 8 demonstrates that the Golden Triangle regions still dominate UK R&D tax credit claims. However, there are some notable exceptions, such as the two Outer London NUTS2 regions featuring in the mid-low end of the distribution, showing the importance of granular detail in regional data. In addition, there is a significant spike for SME R&D tax credit claim amounts in Inner London West. At approximately twice the next highest, this is truly striking and shows the capacity for one NUTS2 region to skew averages at NUTS1 level. Similarly, when measured at NUTS1 level Northern Ireland is the lowest performing region/nation in the UK. However, when taken at NUTS2 level, Northern Ireland falls in the upper-middle part of the distribution. This highlights that while England has the by far the greatest number of R&D-intensive regions, overly-aggregated figures can mask R&D deficiencies in several English regions. This is important because these regions may require targeted place-based R&D support. For example, the North West of England NUTS1 region contains the NUTS2 region Greater Manchester. While Greater Manchester rivals many of the top performing Golden Triangle NUTS2 regions, the North West of England also contains Cumbria, which sits second from bottom of the distribution (just above the Scottish Highlands and Islands).

Taken together, the results from our analysis and the summary statistics in Figure 8 highlight a crucial role for the UK's R&D and innovation grant funding agencies. Some research has made the case that, in contrast to R&D tax credits, specific types of R&D grant may be more appropriate to help firms begin their innovation journey and sustain it through an initial capacity building process (Busom et al. 2014; Perez-Alaniz et al. 2025). This is because firms, and particularly resource constrained SMEs, need upfront capital to de-risk innovation projects (Beck & Demirguc-Kunt 2006; Lee et al. 2015; Chiappini et al. 2022). An implication from analysis suggests that an avenue for shrinking the R&D gap between the Golden Triangle and the rest of the UK may be to focus on the following:

1. Increasing the number of R&D active SMEs in non-Golden Triangle regions, to ensure there are a sufficient number of private sector actors in these regions capable of utilising the highly effective (but nevertheless aspatial and one-size-fits-all) R&D tax credit programme.
2. Nurturing these non-Golden Triangle SMEs' R&D capacity over time, so they can build to claim R&D tax credits at a similar level to SMEs located in the Golden Triangle. This will help ensure that when the effectiveness of R&D tax credits for individual firms is aggregated up to the regional level, the benefits are not inadvertently skewed towards the Golden Triangle.

These points reinforce and highlight the importance of a recommendation from the influential SQW (2022, p. 11) report commissioned by UKRI on place-based research and innovation policy in the UK, which stated the following:

- "In understanding how R&I investment leads to place-based outcomes, we need to understand how and where economic value accrues from different stages of the process. Routes to impact might vary for different places – i.e. primarily through research generation for some places, or via generating and adopting locally, or by adopting locally (but generating elsewhere). This has implications for policy."

In the context of our report, the above point draws out a potentially important implication. It is likely not possible (or desirable) to re-create the conditions of the Golden Triangle in (most) other parts of the UK. However, all regions of the UK contain specific advantages and opportunities which can be built upon and augmented through targeted place-based policy intervention. Indeed, UKRI has already implemented a specific policy intervention which targets this outcome. In 2017, the Strength in Places Fund (SIPF) was announced, to support innovation-led regional growth and enhance local research collaborations (HM Government 2017; McCann 2019; Hughes & Ulrichsen 2019; UKRI 2023). This fund focused primarily on the UK's less R&D intensive regions, providing a relatively small number of projects (12 full-stage projects total) each with a relatively large amount of funding (~£316 million, distributed among the projects). The projects brought together consortia of local SMEs, large and often multinational incumbent firms, and local Higher Education Institutions with specific knowledge bases. This policy design was in an effort to anchor the SIPF R&D funding to well-established local capabilities, augment these capabilities to take advantage of new opportunities, and build a sustainable local innovation ecosystem. Initial policy assessments suggest that the SIPF has been highly successful at improving the innovation system in several regional locations (Luan et al. 2025). This type of holistic, place-based policy intervention may serve as a roadmap for building sustainable research and innovation capacity outside of the Golden Triangle.

There are a broad mix of R&D and innovation policy supports available to firms in the UK. The SIPF and R&D tax credits are just two, which function through different mechanisms and aim at achieving different (but related) policy goals. Within this mix of potential R&D supports for firms, our results suggest that when sustainable, long-term, and place-based R&D capacity building outcomes are achieved by targeted supports such as the SIPF, firms and regions may then be able to reap the full benefits of a highly successful R&D tax credit programme. In this case, the R&D tax credit could usefully continue as it is, with more attention paid to programmes such as the SIPF and other policy initiatives which build a pipeline of R&D-active SMEs to drive sustainable regional innovation performance.

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