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Trade-offs and complementarities between regional, sectoral, and national support policies for firms' innovation

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Public support for R&D can play a crucial role in addressing systemic failures that hinder the functioning of innovation systems, whether national, sectoral, or region-specific. However, little is known about the trade-offs and complementarities between subnational and national innovation policies. Here, we consider trade-offs and complementarities between national R&D support measures managed by UK Research and Innovation (UKRI), regional support provided by the Northern Ireland government, and sectoral support provided by the UK's Catapult network. Using a propensity score matching combined with a difference-in-difference event study analysis, we find evidence of dynamic complementarities between subnational and national innovation policies. Both regional and sectoral innovation support measures have positive effects on both employment and turnover growth. However, each subnational policy targets somewhat different groups of firms to national policy measures. Strong static and dynamic complementarities are also evident between sectoral and national support, as firms initially supported by the Catapults are significantly more likely to secure national R&D funding in the future.

JEL classification: O30, O38, O25

1. Introduction

The innovation system literature argues that innovations flourish not only because of the efforts of the research teams and the organizations behind them but also thanks to the relationships and interactions with a broader system of institutions, knowledge, values, policies, and regulations in the surrounding environment (Lundvall, 1992; Nelson, 1993; Marjanovic *et al.*, 2020; Dworak *et al.*, 2022). This systems perspective suggests that policy intervention can be crucial in integrating the innovation system and addressing system and market failures (OECD, 1999). System and market failure could be addressed through national policy initiatives. However, region-specific (Ruhrmann *et al.*, 2022) or sector-specific market failures (Mohan *et al.*, 2021) may mean that more targeted approaches could be more effective. For instance, region-specific industrial knowledge bases suggest customized regional innovation policies rather than uniform nationally implemented policies (Martin and Trippl, 2014), as in the case of regions with high industrial specialization (Ruhrmann *et al.*, 2022). Similarly, industries face different market failures and would, therefore, require bespoke policy interventions based on their stages of development (Godoe and Nygaard, 2006), ability to exploit agglomeration externalities (Rubalcaba *et al.*, 2010), and different levels of appropriability (Hu and Hung, 2014). Several studies have looked at targeted R&D and innovation policy, in particular, focusing on technology- or industry-specific initiatives (Matti *et al.*, 2017; Mazzucato, 2018; Alstadsæter *et al.*, 2018) or at regional policies (Afcha and García-Quevedo, 2016; Morgan, 2017), to understand their distinct motivations and effects. They have shown that national and subnational R&D support policies target different types of firms, generating heterogeneous additionality effects partly because of the different degrees of overlap between programs (Blanes and Busom, 2004). As a consequence, the concept of the multilevel innovation policy mix (Magro and Wilson, 2013, 2019) implies that policy measures implemented at different administrative levels might interact in unintended ways rather than by design (Flanagan *et al.*, 2011; Martin, 2016; Beņkovskis *et al.*, 2019). Few studies have investigated the differential impact of these policy initiatives. As a result, the empirical evidence on the trade-offs and complementarities of different levels of innovation policy and their effect on business innovativeness and performance remain limited.

To the best of our knowledge, this is the first study to comprehensively assess the impact of regional, sectoral, and national R&D and innovation support policies on business performance and analyze their trade-offs and complementarities. The UK provides an interesting context in which to study such interactions given positive evidence of the effectiveness of innovation support measures (Scandura, 2016; Vanino *et al.*, 2019; Dimos and Vorley, 2024). The UK also performs well in terms of international innovation comparisons, ranking fourth overall in the 2023 Global Innovation Index but second globally in innovation outputs.[1] Our analysis draws on longitudinal data on business performance taken from the Business Structure Database (BSD) and the UK Intellectual Property Office (IPO). To this, we match administrative data on firms' receipt of national R&D and innovation awards funded by UK Research and Innovation (UKRI), regional R&D and innovation awards funded by devolved nations (i.e. Invest Northern Ireland [NI]), and firms' engagement with the sectoral support provided by the Catapult network.

We make two main contributions. First, our analysis allows us to compare the combined effects of national, regional, and sectoral support measures for R&D and innovation using a standard set of evaluation metrics. This adds to the existing literature on the effectiveness of alternative R&D and innovation support measures, which is often fragmented and focuses on the efficacy of single support measures. Second, using an integrated data structure allows us to examine potential complementarities and conflicts between national and subnational sources of R&D and innovation support. In this way, we can assess if subnational support crowds out or substitutes for national support or if the different support measures work in a complementary way. Understanding these potential complementarities has clear policy implications for national, regional, and sectoral measures. It also has implications for policy evaluations: complementarities would suggest that the evaluation of each measure would individually underestimate their total benefits, while trade-offs would suggest overestimating the benefits of each individual scheme. In this way, our analysis contributes to the limited understanding of policy complementarities and conflicts within innovation systems. In addition, we also contribute to the debate in the UK and other developed economies about the need for place-based policies, in particular, consideration of subnational R&D and innovation systems as a means of reducing regional productivity inequalities and contributing to leveling-up (Bailey *et al.*, 2023).

We employ a propensity score matching (PSM) technique combined with a difference-in-difference event study analysis to estimate the differences in growth between comparable firms supported by different R&D and innovation policies. Our assessment considers firm heterogeneity in terms of size, past performance and innovative activities, productivity, and other factors influencing the self-selection of firms into different types of publicly supported R&D projects. Our findings suggest that national, regional, and sectoral R&D support policies can be complementary, mainly by targeting different groups of firms within the business population. Both regional and sectoral innovation support have positive effects on business performance, with regional policy having a significantly stronger effect than sectoral policy on both employment and turnover growth. Regional R&D support is particularly beneficial for the job and turnover growth of smaller firms operating in low-tech industries. In comparison, sectoral measures are

[1] See https://www.wipo.int/edocs/pubdocs/en/wipo-pub-2000-2023-en-main-report-global-innovation-index-2023-16th-edition.pdf, 204.

more beneficial for larger high-tech manufacturing firms. This is also reflected in the effects on firms' innovation, as sectoral support has a stronger impact on firms' patenting. Strong dynamic complementarities are also evident between sectoral and national support, as firms supported by the Catapults are significantly more likely to secure national R&D funding in the future.

The remainder of the paper is organized as follows. Section 2 specifies our conceptual framework. Section 3 outlines the UK policy landscape concerning the national, regional, and sectoral context. Section 4 presents the related hypotheses from the conceptual framework and the UK-specific policy context. Section 5 describes our data and methodology, and Section 6 presents the key results from our empirical analysis. Section 7 discusses the implications and concludes.

2. Conceptual foundations

2.1. The policy mix of national and subnational R&D support measures

The combination of national and subnational R&D and innovation support measures can be conceptualized as a multilevel policy mix, with different justifications applying to adopting national and subnational policies (Magro and Wilson, 2013, 2019; Anderton, 2017). At the national level, policy intervention to support R&D and innovation is typically justified by market or system failures linked to structural characteristics of the national economy, regulatory frameworks, or institutional norms (Woolthuis *et al*., 2005). Regional R&D and innovation support measures have been considered through the lens of regional innovation systems (Cooke *et al*., 1997), with intervention justified by spatially distinct system or market failures (Coenen *et al*., 2017). For example, institutional failures and/or sparse networks may create localized bottlenecks to innovation requiring distinct responses (Todtling and Trippl, 2013). In more peripheral regions, attention has focused on the regional innovation paradox: "less developed regions have a greater need for innovation-related investment, they also have a lower capacity to absorb public funds earmarked for innovation compared to economically more advanced regions" (Morgan, 2017: 570). Regional policies may then create an advantage by building on the availability of regionally specific knowledge bases (Asheim *et al*., 2011), with objectives more closely aimed at developing technological clusters and broadening the base of local firms conducting R&D (Afcha and García-Quevedo, 2016). This leads directly to the recent discussion about smart specialization (Morgan, 2017). However, conceptualizations of regional innovation systems and smart specialization have been criticized as lacking micro-foundations and an awareness of the firm-level incentives and capabilities that might shape innovation (Uyarra, 2010). Morgan (2017) also suggests that discussion of regional innovation would also benefit from closer integration with the literature on entrepreneurship, "which aims to restore the themes of agency, interests and power to the centre of organisational analysis" (Morgan, 2017: 581).

Since its inception, the literature on sectoral innovation systems has engaged more closely with issues around agency and entrepreneurship to provide a "multidimensional, integrated and dynamic view of sectors" (Malerba, 2002: 248). As such, sectors and sectoral innovation systems may be subject to transformational changes due to technical change, disruptive innovation (Yu and Hang, 2010), or entrepreneurial entry (Roper and Hewitt-Dundas, 2017). New technologies or business models may also create new sectors competing with or complementing existing industries. In their emergent phases, new sectors, and the technologies on which they depend, involve significant market failures, which justify intervention (Van Alphen *et al*., 2009). For example, Matti *et al*. (2017) consider the effects of multilevel policy (e.g. sectoral, energy, and innovation) on the success of the development of the wind energy sector in Spain, stressing the importance of policy intervention during the early years of development. As Malerba (2002: 262) suggests, "public policy proposals may be developed on how to affect the transformation of sectoral systems, … [overcome] mismatches and blocks that parts of the system exert on the rest."

Policy mix approaches also recognize the potential for sectoral failures in terms of directionality, demand articulation, policy coordination failure, or reflexivity (Weber and Rohracher, 2012). Directionality failures can occur when sectoral trajectories develop so as to fail to address broader social or global challenges. Failures in demand articulation may occur where prospective markets are defined by narrow niches that provide inadequate returns or where returns are so uncertain that innovation investments are hard to justify. Policy coordination failures may occur within or across levels in a multilevel policy mix and reflect the creation of perverse or conflicting incentives. Finally, reflexivity failures occur when ecosystem organizations cannot identify system failures and then address them. As Matti *et al.* (2017: 664) suggest: “Taking a policy mix approach implies a need to pay attention to potential interactions, conflicts and tensions between goals, rationales, instruments and implementation approaches of different instruments at different levels and at different times.” Thus, there is an increasing acknowledgment of the importance of comprehensively considering multilevel innovation policy mix (Magro and Wilson, 2013, 2019) and vertical R&D policy interactions (Ghazinoory *et al*., 2019). Different innovation policies might have different rationales and objectives, resulting in heterogeneous impacts on businesses. The range of policy measures implemented at different levels could interact with each other, resulting in complementarities between these policies or in a trade-off where one policy could crowd out another policy’s impact (Flanagan *et al*., 2011; Cunningham *et al*., 2016; Martin, 2016; OECD, 2020).

2.2. From R&D policy mix to business growth

The existing literature has identified four mechanisms that may link public R&D and innovation support to increased innovation activity and business performance. First, public R&D and innovation support will increase liquidity and financial slack in recipient companies, which may help overcome innovation’s perceived risks (Zona, 2012). Second, through cost-sharing, public support for private R&D and innovation reduces the required investment, de-risks private investment, and increases anticipated post-innovation returns (Mechlin and Berg, 1980; Calantone *et al*., 2010). A similar mechanism may also operate where R&D and innovation support stimulate demand in emerging technologies or situations with inadequate private but substantial social benefits (Mazzucato, 2016). Third, public R&D and innovation support can play an enabling or bridging role, helping firms to access otherwise unavailable knowledge. Innovation vouchers, for example, incentivize firms to approach knowledge providers, something they may otherwise not have done (OECD, 2020). Similarly, publicly supported collaborative R&D and innovation projects may enable knowledge transfer and create dynamic complementarities as innovating firms develop new routines to benefit future innovation projects (Love *et al*., 2014; Roper and Hewitt-Dundas, 2015).

In situations where firms can access both national and subnational R&D and innovation support measures, Douglas and Radicic (2020) suggest that three outcomes may arise: complementary or synergistic effects, trade-offs where one policy intervention reduces the impact of the other(s), and neither complementarity nor trade-off effects. For instance, Blanes and Busom (2004) investigated which firms participate in national and regional subsidy programs, finding that these schemes reach different populations of firms. (Afcha and García-Quevedo, 2016) have shown that both national and regional subsidies lead to the hiring of more R&D employees. However, the magnitude of the national subsidy effect is double that of the regional subsidy. On the contrary, Bedu and Vanderstocken (2020) found that regional support has no significant impact on the R&D employment of small and medium enterprises (SMEs), contrary to national subsidies. Similarly, inconclusive is the evidence on the effect of R&D public support on R&D cooperation between universities and private partners. While Fernández-Ribas (2009) found positive effects from regional and national support, Afcha and López (2014) found no effect.

Complementary and trade-off effects may also have both static and dynamic aspects and be influenced by the targeting of different groups of firms. Static complementarities or trade-offs occur where national and subnational R&D and innovation measures enhance or offset different aspects of firms’ innovation activities within a single period. For example, Douglas and Radicic (2020) explore static complementarities between regional and national sources of R&D support in Spain. Looking at behavioral additionality effects, they find strong policy mix complementarities for SMEs regarding the extent of cooperation but weaker complementarity effects for larger firms. Similarly, Czarnitzki and Lopes-Bento (2014) identify positive complementarities between EU and national innovation support measures for German firms for both input additionality and the quality of innovation outputs. Italian data suggest positive complementarities between innovation advisory services and innovation vouchers (Caloffi *et al*., 2022). (Becker *et al*., 2017) have looked at the effectiveness of regional, national, and EU innovation support in promoting firms' innovation activity in Spain and the UK, finding that regional support is most influential in promoting process innovations, while national support is associated with a higher probability of product innovation. Acerbo and Miguel-Davila (2024) also use Spanish data to explore the innovation benefits of EU, national, and regional policy instruments, finding that different policy instruments are associated with varied innovation outcomes facilitating synergies between policy levels (see also Mulligan *et al*., 2019). However, evidence for China suggests the potential for both trade-offs and complementarities between national and regional support measures (Shi *et al*., 2023).

Except for the recent study by Caloffi *et al.* (2022) on Italy, most other empirical evidence on static complementarities in the policy mix relates to grant support for R&D and innovation. Here, support from multiple sources may reinforce crowding-in effects, allowing firms to make larger-scale R&D and innovation investments or take on projects that would otherwise have been beyond the business's resources (Mulligan *et al*., 2019). Trade-offs may also arise if firms are over-subsidized, leading to inefficient funding allocation or use (Catozella and Vivarelli, 2012). Different subnational/national policy mix elements may help firms to access complementary knowledge bases. However, related trade-offs may also arise if knowledge flows become unmanageable due to limited managerial cognition or coordination capacity. This possibility mirrors the "over-search" problem in innovation collaboration and the widely observed inverted U-shaped relationship between partner numbers and their innovation benefit (Laursen and Salter, 2006; Vahter *et al*., 2014).

Dynamic complementarities or trade-offs may occur when the receipt of one measure enhances or reduces the effects of other interventions in subsequent periods. For example, Roper and Hewitt-Dundas (2015) suggest that firms' investments in knowledge stocks in one period benefit knowledge search capability and innovation outputs in subsequent periods. Subnational R&D or innovation grants that help firms develop capabilities in one period may, therefore, enhance the future benefits derived from either national or further subnational grants. Experience in one R&D or innovation grant scheme has also been shown to increase the probability of future grant receipt. Huergo and Ubierna (2015), for example, show that for Spanish firms, the experience of "other" grant schemes increased the probability that firms would subsequently obtain low-interest loans for R&D. Essentially similar findings have also been reported for Italy (Antonelli and Crespi, 2013), Spain (Busom *et al*., 2017), and Finland (Karhunen and Huovari, 2015). These links may reflect firms' cumulative knowledge assets, learning in compiling grant applications, or signaling benefits related to the previous grant awards. Trade-offs or inefficiencies may also occur where the combination of national and subnational support leads to firms being over-subsidized, insulating managers from market realities, encouraging inertia or poor resource allocation toward risky projects (Nohria and Gulati, 1997), and increasing grant dependency (Kilponen and Santavirta, 2007). Most of these studies rely on surveys of R&D-intensive firms, an unrepresentative sample of the business population, with limited information on the R&D support schemes considered at different levels, limiting the analysis of the interactions, complementarity, and trade-offs between policies.

Synergies between subnational and national policy measures may also arise when each policy targets different groups of firms or sectors. Such targeting may reflect the specific business demographics of a region or industry and the differential support needs of various types of firms (Bergek and Norrman, 2015). Alternatively, synergies may arise as support targeted at firms in one element of a supply chain generates knowledge spillovers, driving innovation, and productivity gains elsewhere (Becker *et al*., 2023).

3. UK policy context

The UK has a mature and complex support framework for business R&D and innovation, combining a range of national, regional, and sectoral initiatives (Lenihan *et al*., 2020).[2] At a national—UK-wide—level, the Research Councils operating under the umbrella of UKRI have

[2] For a detailed overview see:

Table 1. Overview of national, regional, and sectoral support measures

Scope	Delivery organization	Support measures	Allocation process
National	UKRI (including Innovate UK)	R&D and innovation grants and loans, collaborative projects, fellowships	Competition-based
Regional	Invest NI	R&D and innovation grants	Negotiated
Sectoral	Catapult Network	Collaborative R&D projects	Negotiated

provided a consistent source of support for R&D and innovation over the last two decades, with Innovate UK providing the bulk of direct innovation grants and loans to firms (Table 1). Other Research Councils primarily support R&D in UK universities, with business–industry collaboration a particular focus of the Engineering and Physical Sciences Research Council (EPSRC) and the Medical Research Council (MRC).[3] In 2020/2021, UKRI provided a total of £3.1bn in grant spending, supporting around 4700 individual research projects allocated through national open competitions. Of this, Innovate UK made 1410 grants and loans directly to firms, totaling commitments of £885m in 2020/2021 or around £13.1 per capita across the UK.[4] Earlier studies have pointed to the crowding-in effects of EPSRC support on private sector R&D spending (Scandura, 2016) and the positive business growth effects of UKRI support (Vanino *et al.*, 2019). In addition to R&D and innovation support provided through UKRI, firms across the UK are also able to access substantial R&D tax credits, spending on which has increased sharply in the UK in recent years to a level higher than that in any other countries part of the Organization for Economic Cooperation and Development (OECD) (Lenihan *et al.*, 2020), with positive effects in terms of both R&D and patenting and of spillovers to related firms (Dechezleprêtre *et al.*, 2016; Bösenberg and Egger, 2017).

Alongside the UK-wide support provided by UKRI, a range of regional and local support measures for R&D and innovation have existed and do exist across the UK (Table 1). During the period before 2012, significant regional incentives were available across all parts of the UK through the devolved administrations in Scotland, NI, and Wales and the Regional Development Agencies (RDAs) in England. The run-down and closure of the RDAs over the 2010–2012 period led to the centralization of R&D and innovation support measures in England with Innovate UK but left intact the regional supports for R&D and innovation provided by the devolved administrations (Scotland, Wales, and NI). Since 2012, this means that the most significant regional innovation support measures available in the UK are those operated by the devolved administrations. In Scotland, Scottish Enterprise has provided R&D grants although this has recently shifted toward an emphasis on supporting the green transition.[5] In Wales, innovation and R&D are supported through Business Wales' SMARTCymru service, which provides advisory support and limited funding support through innovation vouchers.[6] In NI, both innovation and R&D grant support is provided by Invest NI through innovation vouchers and larger follow-on R&D grants (Table 1).[7] As a result, firms located in the devolved nations have access to both regional and national support for R&D and innovation. Directly comparable budgets for each of the Devolved Territories are not available, but for NI, total R&D and innovation grants in 2018–2019 totaled £57.7m (£30.4 per capita),[8] an "Innovation and industries" budget line in

https://assets.publishing.service.gov.uk/government/uploads/system/uploads/attachment_data/file/1023586/evidence-for-innovation-strategy.pdf.

3 See https://www.ukri.org/about-us/.

4 See https://www.ukri.org/what-we-offer/what-we-have-funded/innovate-uk/.

5 See https://www.scottish-enterprise.com/support-for-businesses/funding-and-grants/business-grants/research-and-development-grant.

6 See https://businesswales.gov.wales/expertisewales/support-and-funding-businesses/smartcymru.

7 See https://www.investni.com/support-for-business/funding-for-innovation-and-research-and-development.

8 Source: Invest NI.

Scotland for 2020/2021 was £62m (£11.3 per capita),[9] and in Wales, the annual innovation grant and advisory budget over the same period was around £9m pa (£2.9 per capita).[10]

Sectoral R&D and innovation support measures have a more recent history in the UK, assuming greater importance in recent years through the post-2017 Industrial Strategy Challenge Fund.[11] One of the key sectoral support measures is the Catapult network, a group of nine technology and innovation centers supported through Innovate UK. Initially introduced following the Hauser Review of 2010 (Table 1),[12] the Catapult network provides physical R&D facilities to support business innovation across a range of sectors, from high-value manufacturing to digital and satellite technologies.[13] Government support for the Catapult network totaled £196.8m in 2020/2021 (£2.9 per capita).[14] As with firms located in the devolved nations of the UK, firms in the sectors to which the Catapults are relevant can access support for R&D and innovation from both UKRI and the relevant Catapult.[15]

4. Hypotheses

Our first two hypotheses relate to the business benefits of subnational and national policy measures. H3 relates to the potential complementarities and trade-offs (targeting, static, and dynamic) that might be created by national and subnational policy measures (Douglas and Radicic, 2020).

A large body of literature provides positive evidence on the relationship among public R&D support, innovation, and business performance (Zuniga-Vicente *et al*., 2014; Becker, 2015; Cunningham *et al*., 2016). In a UK context, Vanino *et al*. (2019) also provide positive evidence of the medium- and long-term effects on business growth when firms participate in UKRI-funded projects. As indicated previously, such projects may either be collaborative university–business R&D projects, in which the firm gains knowledge but no direct financial benefit, as in the case of sectoral support from the Catapults, or direct R&D or innovation subsidies where the firm is a direct financial beneficiary, as in the case of regional Invest NI grant support measures. In the case of Invest NI R&D grant support, growth may be driven by de-risking R&D and innovation projects, increasing liquidity and financial slack, or by enabling access to otherwise unavailable resources. However, growth benefits from sectoral innovation support provided by the Catapults will rely on knowledge transfers or knowledge creation. The combination of both financial and knowledge creation mechanisms generated by regional grant support suggests that this may have stronger innovation effects than sectoral support measures. This, and the evidence from the UK and other countries, suggests our first hypothesis:

H1: Business growth effects of subnational R&D and innovation support measures.

Subnational R&D and innovation support measures, whether direct subsidies or collaborative projects, will have positive, medium-term effects on business growth.

Few studies have compared the scale of impacts of national and subnational innovation support measures. On an international scale, Czarnitzki and Lopes-Bento (2014) find no difference in the effects of national and EU support on innovation in German firms. However, Becker *et al*. (2017) compare the innovation benefits of regional and national R&D subsidies in the UK and

[9] https://www.gov.scot/publications/scottish-budget-2020-21/documents/.

[10] There are no directly identified data available on R&D and innovation support measures, but over the 2014–2023 period, a dedicated public budget (including Welsh Government and ERDF funding) for supporting business R&D and innovation totaled £78.4m, an annual average of around £9m. See https://business.senedd.wales/documents/s98329/CYPE5-05-20%20-%20Paper%20to%20note%204.pdf.

[11] See https://www.ukri.org/what-we-offer/our-main-funds/industrial-strategy-challenge-fund/.

[12] https://catapult.org.uk/wp-content/uploads/2020/12/Hauser-Report-of-Technology-and-Innovation-Centres-in-the-UK-2010.pdf.

[13] There are currently nine Catapults related to Cell and Gene Therapy, Compound Semiconductor Applications, Connected Places, Digital technologies, Energy Systems, High Value Manufacturing, Medicines Discovery, Offshore Renewable Energy, and Satellite Applications. See https://catapult.org.uk/about-us/our-centres/.

[14] Source: https://www.ukri.org/publications/innovate-uk-funded-projects-since-2004/. Filtered for year of award and setting "Enterprise Size" to "Catapult."

[15] If in the devolved nations from the regional support agencies.

Spain and find differential effects. In both countries, national support measures have more substantial impacts on product/service innovation, while regional support measures have stronger effects on process, organizational, and strategic innovation. Becker *et al*. (2017) suggest that this might be linked to the different rationales for intervention that apply to national and subnational support measures, as well as their different allocation mechanisms.

In the UK context, approaches to providing grant support for R&D and innovation differ significantly between regional support provided in NI and national UK support measures. This distinction may influence the quality of projects supported and the "fit" between the support provided and firms' funding requirements. In NI, a network of Client Executives or Client Managers facilitates grant support to firms. Giving evidence to the NI Assembly Economy Committee, June 29, 2016 (10), Jeremy Fitch, MD of Business International, Invest NI, described the operation of the Client Executive system as follows[16]:

> Their job is to understand the business.… We will go into the business, have a look at it and say, 'What issues do you face? What opportunities are there? What impediments are there?' From that, the client manager or client executive agrees with the company a range of solutions that we can provide to those issues. It may be something to do with skills—can we offer skills? It may be something to do with research and development to develop a new product,… The client executive works with the business and agrees the priorities, and then we provide a solution.

The negotiated approach to supporting R&D and innovation in NI contrasts sharply with the delivery of national support, which is through open and competitive calls for proposals (Table 1).[17] We envisage that the potential for a better match between subnational support and firms' individual needs may strengthen these effects, suggesting our second hypothesis:

H2: The relative impacts of subnational and national R&D and innovation support measures.

Subnational R&D and innovation support measures will be better suited to the particular needs of individual firms and will, therefore, have stronger positive effects on business growth than national support measures.

Douglas and Radicic (2020) suggest that complementarities or trade-offs may arise when national and subnational R&D and innovation support measures form a multilevel policy mix. Conceptual arguments suggest that complementarities may arise when policies address different elements of firms' innovation process, target different groups of firms, or are planned to enhance another. Trade-offs are more likely when measures are introduced without a system-wide perspective or a lack of coordination (Magro *et al*., 2014; Howlett and Del Rio, 2015). Existing empirical evidence on the additionality effects of a multilevel policy mix is limited and relates either to complementarities/trade-offs between national and supranational policy interventions (Czarnitzki and Lopes-Bento, 2014) or comparisons of the effectiveness of policy intervention at different levels (Fernández-Ribas, 2009; Becker *et al*., 2017). However, neither study provides specific evidence on whether complementarity or trade-off effects are more likely between national and subnational levels. We also have little prior evidence on targeting complementarities, which may arise when national and subnational policy support targets different groups of companies (Bergek and Norrman, 2015; Becker *et al*., 2023). As suggested, targeting effects are likely linked to potential knowledge transfers. At the same time, static and dynamic complementarities are related to the impact of public support in de-risking innovation, enabling knowledge creation or enabling access to new external resources. Based on the discussion in Douglas and Radicic (2020), we hypothesize that

[16] http://data.niassembly.gov.uk/HansardXml/committee-18 356.pdf.

[17] This approach to business support is similar to the Account Management system operated by Scottish Enterprise. Evaluations of the Scottish Account Management system have stressed the value placed by businesses on the relationships involved and pointed to stronger additionality (although with smaller absolute effects) among smaller firms (Slims Consulting, 2009).

H3: Complementarities between policy levels.

H3a: Targeting complementarities for business growth may result from subnational and national policy measures more effectively supporting different subgroups of firms.

H3b: Static complementarities for business growth may result when firms receive both national and subnational R&D or innovation support.

H3c: Dynamic complementarities may result when firms receive subnational support prior to national R&D and innovation support.

5. Data and methodology

5.1. Data sources

We analyze three policy initiatives to examine the business growth effects of regional and sectoral R&D and innovation support measures and their complementarities with national support. The regional policy relates to the support provided in NI by Invest NI, while the sectoral policy relates to the support provided by the Catapult network. Both policy initiatives are compared with national R&D grant support provided by UKRI. Data for each policy initiative are matched with firm-level data from the Office of National Statistics (ONS) BSD covering the whole population of businesses in the UK between 1997 and 2020 (ONS 2024). The BSD provides information on firms' age, ownership, turnover, employment, and industrial classification at the Standard Industrial Classification (SIC) four-digit level and postcode. In addition, we use data from the UK IPO on the number of patents registered annually by each firm in the UK over the same period. We matched these databases using the Company Reference Numbers (CRNs) provided in each dataset.

5.1.1. National support

Data on UKRI-funded projects are taken from the Gateway-to-Research (GtR) website.[18] GtR provides information on all publicly funded research projects over the 2004–2016 period, including data from Innovate UK, the seven Research Councils, and the National Centre for the Replacement, Refinement, and Reduction of Animals in Research. GtR also provides information about approximately 34,000 organizations that participated in publicly funded innovation and R&D projects, including details on the number and value of funded projects, the number and characteristics of partners, the topics and outcomes of the research projects, the value of grants awarded per year, the Research Council providing the funding, and information about each project's leaders.[19]

5.1.2. Regional support

To analyze regional support policy, administrative data on individual grant awards for R&D and innovation were made available by Invest NI covering the period 2006–2019. During this period, 8202 awards were made available, 5315 for innovation and 2887 for R&D projects. For most grant recipients, CRNs were available. Where these were not included, these were added from Companies House and the Financial Analysis Made Easy database. These data were then matched with the BSD dataset, excluding those organizations with no CRNs (unmatched or unnamed firms, not-for-profit organizations, etc.), other UK firms not located in NI, and other foreign companies. After the matching, our final matched sample includes 66% of the total number of R&D and innovation Invest NI grant beneficiaries.

The number and value of regional R&D grants increased rapidly from 2006 to 2009 before stabilizing, although the number of new R&D awards declined somewhat after 2015, as shown in Figure 1. The time profile of innovation grants suggests a somewhat different pattern, peaking around 2014 in the number of awards but increasing steadily in value. Table 2 shows that Invest NI mainly supports micro (less than 10 employees) and small enterprises (less than 50 employees), representing more than 85% of all firms supported. This evidence indicates that support from

[18] We abstracted the data for this study between January 2 and 5, 2017, from the GtR website available at the following link: https://gtr.ukri.org/.

[19] More detailed information on the GtR database is provided by Vanino *et al*. (2019).

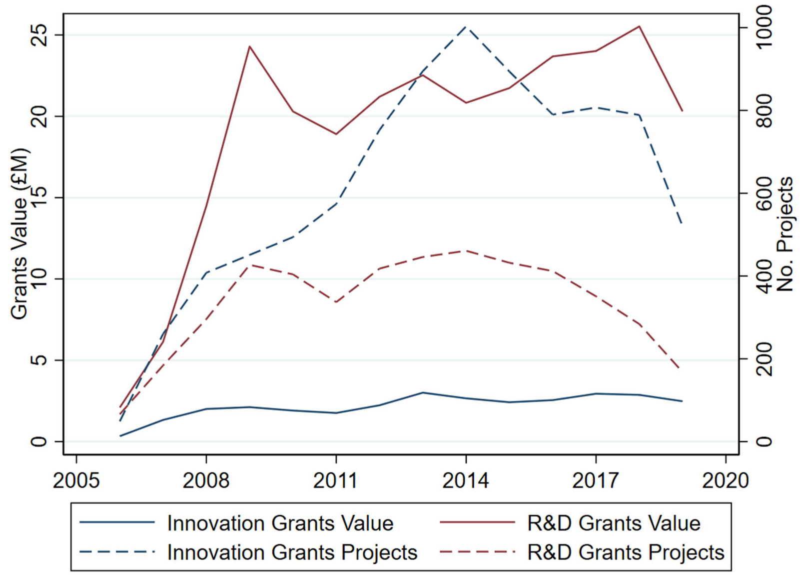

Figure 1. Evolution of Invest NI R&D and innovation grants for private firms. *Note*: Statistics based on administrative data from Invest NI and the ONS BSD. These statistics are based on the sample of Invest NI supported firms matched with the BSD.

Table 2. Distribution of Invest NI grant funding by firm size

Size	No. of firms	Grants value (£)	Per-business value (£)
Micro	3228	108,941,848.5	33,750
Small	1535	67,534,276.8	43,996
Medium	557	40,946,411.6	73,512
Large	137	61,825,157.5	451,278

Statistics based on administrative data from Invest NI and the ONS BSD. We define micro enterprises as firms with fewer than 10 employees, small firms as those with 10–49 employees, medium are firms with 50–250 employees, and large firms as those with more than 250 employees.

Invest NI is mainly to help smaller firms to get involved with R&D and innovation. If we consider instead the value of grants awarded by firm size distribution, we observe that while micro firms receive the largest amount of funding overall, the average grant per company is much smaller than that for other supported firms, around £33,000. This aligns with the general size distribution of firms involved in UKRI-funded R&D projects analyzed in previous studies (Scandura, 2016; Vanino *et al.*, 2019), where larger firms usually attract most of the funding.

From a sectoral perspective, Figure 2 shows a strong clustering of regional support in relatively few, and not particularly high-tech, sectors. For instance, the retail sector accounts for the largest number of funded projects, followed by IT, professional services, and construction in the service industry. In manufacturing, the metals, machinery, chemical, and food sectors attract the largest number of projects. However, regarding grant value, the retail sector attracts only a limited amount of funding, thus receiving small R&D and innovation support from Invest NI but for many smaller grants. On the contrary, most of the funding is attracted by professional services, electronics, IT, and financial services. This trend is driven by firms in the financial services and electronics manufacturing sectors, where a few firms secured very large R&D and innovation grants from Invest NI.

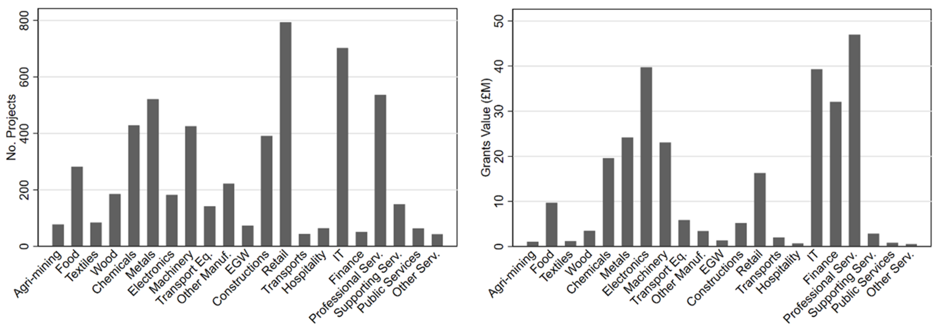

Figure 2. Industrial distribution of Invest NI R&D and innovation supported projects and grants value. *Note*: Statistics based on administrative data from Invest NI and the ONS BSD. Sectors definition based on the SIC 2007 two-digit industrial classification.

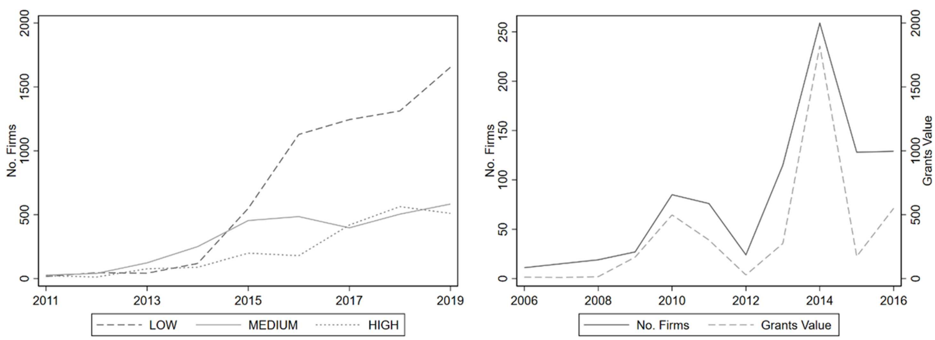

Figure 3. Evolution of Catapult network engagement and UKRI-funded projects with Catapults partners. *Note*: Statistics based on administrative data from the Catapult network, the GtR data, and the ONS BSD.

5.1.3. Sectoral support

For the sectoral support policy, Innovate UK compiled and provided administrative data on firms' engagement with the Catapult network over the period of 2011–2019. These data provided the name and CRN of firms engaging with the Catapult network, the year of the interaction, the specific Catapult contacted, as well as the overall level of engagement, assessed by the Catapults as low, medium, or high. In this analysis, we focus on the impact of medium- to high-intensity engagement with the Catapult network. Over the 2011–2019 period, Catapults were engaged in around 23,000 activities with firms, of which almost 9500 engagements reported as medium–high intensity were matched to the BSD database.

As shown in Figure 3, Catapults' engagement with firms increased after 2014, with a rapid increase in low-engagement activities. However, "high engagement" of firms overtook "medium engagement" around 2017, demonstrating increasing engagement intensity between firms and the Catapult network. Considering the graph on the right-hand side of Figure 3, we can also observe that the collaboration of Catapults with firms in national-level UKRI-funded research projects has rapidly increased since 2012, in terms of both the number of private partners and the value of grants awarded, highlighting an increased intensity in the participation of Catapults in UKRI-funded partnerships.

Table 3 shows that Catapults mainly engage with micro (fewer than 10 employees) and small enterprises (less than 50 employees), representing three quarters of the entire population of firms supported. This evidence is indicative of the type of sectoral-focused activities supported by the Catapult network, mainly helping smaller firms to get involved with R&D activities and innovation. When we look instead at firms partnering with Catapults in nationwide UKRI-funded

Table 3. Distribution of high engagement with the Catapult network and UKRI-funded projects with Catapults partners by firm size

	High	UKRI projects	
Size	Engagement	No. of firms	Grants value
Micro	1064	239	1028
Small	478	211	1018
Medium	278	176	667
Large	266	290	1403

Statistics based on administrative data from the Catapult network, the GtR data, and the ONS BSD. We define micro enterprises as firms with fewer than 10 employees, small firms are those with fewer than 50 employees, medium are firms with fewer than 250 employees, and large are firms with more than 250 employees.

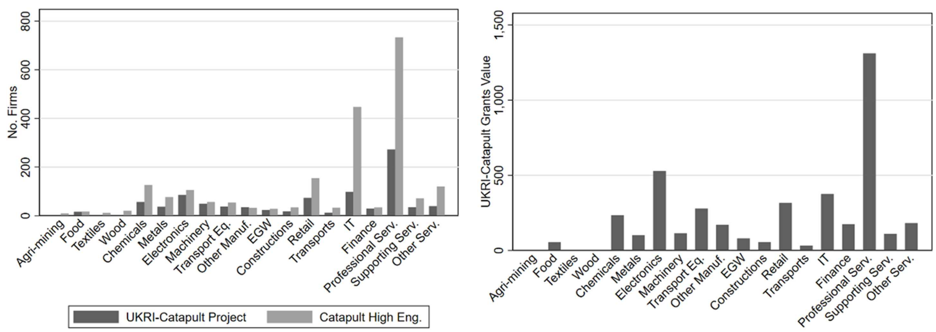

Figure 4. Industrial distribution of high engagement with the Catapult network and UKRI-funded projects with Catapults partners. *Note*: Statistics based on administrative data from the Catapult network, the GtR data, and the ONS BSD. Sectors definition based on the SIC 2007 two-digit industrial classification.

R&D projects, we observe that the size distribution is entirely different, with a more equal distribution between SMEs and large firms, where the latter (more than 250 employees) account for the largest share in terms of both the number of companies supported and the overall value of UKRI grants captured. This aligns with the more general size distribution of firms involved in UKRI-funded R&D projects analyzed in previous studies (Scandura, 2016; Vanino *et al.*, 2019), with a predominance of larger firms supported, especially by EPSRC and MRC.

Given the sector-oriented strategy of the Catapult network, in Figure 4, we identify a concentration of firms' engagement with Catapults in a few high-tech industries. In particular, a large proportion of engaged firms are in the services sector, mainly focusing on information and communication technology (ICT) and professional services. In manufacturing industries, firms engaging with the Catapult network mainly operate in the chemicals and electronics sectors. Also, regarding the value of UKRI grants captured by companies collaborating with the Catapults, we observe a similar distribution, with a higher value of grants going to companies in the professional services sector and the electronics and transport equipment manufacturing sectors. However, the industrial distribution of UKRI-funded firms collaborating with Catapults differs from the sectoral composition of UKRI-funded firms analyzed in previous studies (Vanino *et al.*, 2019). Firms collaborating with Catapults in UKRI-funded projects are mainly operating in the ICT sector and in professional services. At the same time, as Vanino *et al.* (2019) have previously shown, UKRI-funded firms mainly operate in manufacturing industries.

5.2. Methodology

The probability of a firm receiving support will be affected by endogenous factors influencing the self-selection of firms into funding or funding allocation mechanisms. To overcome this issue, we apply a PSM technique at the firm level, as developed in previous studies facing similar empirical challenges (Scandura, 2016; Vanino *et al*., 2019), combined with a staggered difference-in-difference event study analysis (Callaway and Sant'Anna, 2021). This allows us to create a suitable control group of non-treated firms that is as similar as possible to that of treated firms based on the likelihood of being supported. We then compare differences in growth outcomes between supported and untreated firms over time using a staggered difference-in-differences event study analysis. This technique is particularly suitable for dealing with observations treated at different points in time to check the validity of the pretreatment parallel trend assumption and analyze the dynamic evolution of the treatment over time (Callaway and Sant'Anna, 2021).

We focus on the impact of the first-time support provided to a firm to better identify the causal effect (Scandura, 2016). The fundamental problem in this type of analysis is the self-selection of firms into the treatment, causing estimates to be biased if this issue is not appropriately addressed. Hence, we need to build a suitable control group by considering the effect of no treatment on the performance growth of similar firms which did not receive the support. To build suitable control groups, we use a propensity score nearest-neighbor matching technique to select the most appropriate control unit for each treated company from the large group of untreated firms, matching observed characteristics as closely as possible to those of treated firms before the beginning of the R&D and innovation support (Vanino *et al*., 2019). We estimate the probability of receiving support, the so-called propensity score, based on a set of observable characteristics that influence the likelihood of receiving support for R&D or innovation in previous studies. For each treatment, we use a probit model with industry- and year-fixed effects to estimate the propensity score for all observations, using several covariates that may explain the probability of firm i receiving support, as shown in equation (1). We include a set of firm-level variables (X_{it-n}) such as the lagged value of employment and turnover, firm age, employment and productivity growth in the 2 years before the treatment, firms' market share, group membership, foreign ownership and single-plant firm dummies to control for firms' characteristics, and the lagged stock of patents to control for firms' previous innovation activities. In addition, we consider other control variables at the industry s (SIC two-digit) and region r (travel To work area) level (K_{rst}) to control for location- and sector-specific factors, such as the agglomeration index, employment and turnover per employee, entry rate, and share of treated firms. Finally, we also include year (γ_t) and industry (γ_s) fixed effects:

$$\Pr(T_{it}) = \alpha_0 + \alpha_1 X_{it-n} + \alpha_2 K_{rst} + \gamma_t + \gamma_s + \varepsilon_{it}. \tag{1}$$

We estimate a separate propensity score for each treatment to consider the heterogeneous likelihood of being treated for firms with different characteristics. The assignment to treated and untreated groups differs in the hypothesis being considered. Our baseline analysis considers the impact of receiving support from subnational R&D and innovation measures relative to untreated firms (H1). For the regional support baseline analysis, we draw a sample of untreated firms from the general population of NI firms operating within the same industry. We then compare the difference in business growth between firms funded by Invest NI and those receiving no such support. For sectoral support, we consider the impact of medium- to high-intensity engagement with the Catapult network and draw a control sample of untreated firms from the general population of firms operating within the same industry and region.

Once these baseline facts are established, we proceed by evaluating the relative impact of subnational and national R&D and innovation support measures on firms' performance to assess whether subnational R&D and innovation policies are better suited than national support to the needs of individual firms and will therefore have more substantial positive effects on business performance (H2). This is done following our baseline specification, using in this case for firms treated with regional and sectoral support a control group of comparable firms that have only received national R&D and innovation support from UKRI.

We also perform additional analysis to investigate the specificities of regional and sectoral policies and understand the trade-offs or complementarities between national and subnational public R&D support policies (H3). In particular, we first explore the heterogeneity of these effects by differentiating between firms operating in manufacturing and services sectors, high-tech and low-tech companies,[20] and micro-small and medium-large enterprises. This will help us understand if national and subnational support could be complementary by targeting their support at different firm subgroups (H3a). Second, we test the presence of static complementarities for business performance resulting from receiving both national and subnational R&D or innovation support (H3b). For this, we evaluate the effect of holding jointly a UKRI and an Invest NI R&D grant for regional support, while we consider the impact of collaborating in a UKRI-funded R&D project with a Catapult as a partner for the sectoral policy. In both cases, we include as controls untreated firms participating in other UKRI-funded projects which have not received regional or sectoral support. Finally, we analyze possible dynamic complementarities between R&D support policies at different levels, where subnational support could lead to accessing national R&D and innovation support (H3c). To do this, we estimate whether firms receiving regional or sectoral support are more likely to receive national R&D funding in the future compared to suitable control groups of untreated companies.

Tables A1 and A2 report the results of the propensity score estimation for the baseline analysis for both subnational support policies, which are consistent with previous studies.[21] In particular, large, more productive, and younger firms are more likely to be supported, particularly if located in highly agglomerated and productive regions and industries. To check the propensity score balancing, we report mean differences across the treated and control groups for the set of variables used to estimate the propensity score after matching. Where differences between treated and untreated firms were observed before matching, these are significantly reduced after matching. The bias after matching for all covariates is reduced below the 25% critical threshold, and the *t*-values for differences in the means are not significant, suggesting a consistent and balanced matching and that there are no systematic differences in the observable characteristics of matched treated and untreated firms before receiving regional or sectoral support. The matching procedure satisfies the balancing property, suggesting that the conditional independence assumption is not violated.[22]

After we have built a suitable group of untreated control firms for each treatment, we estimate the following difference-in-differences model to analyze the causal impact of subnational support on several measures of firms' performance:

$$Y_{it} = \alpha_0 + \alpha_1 T_{it} \times P_{it} + \alpha_2 X_{it-n} + \alpha_3 K_{rst} + \gamma_i + \gamma_t + \gamma_s + \varepsilon_{it}, \qquad (2)$$

where Y_{it} represents different measures of firm i performance in year t, as the log of employment, turnover, and patents registered. The main coefficient of interest is α_1, estimating the impact of the treatment (T_{it}) for firm i after being treated (P_{it}) with respect to untreated firms. We also control for the same variables used in our propensity score estimation, including a set of firm-level (X_{it-n}) and industry-region-level control variables, together with firm (γ_i), year (γ_t), and industry (γ_s) fixed effects.[23] Finally, we estimate the difference in the performance of supported

[20] Following the ONS-Eurostat classification, we consider the following as high-tech firms in the SIC 2007 industries: (20) chemicals; (21) pharmaceuticals; (26) computer, electronic, and optical products; (27) electrical equipment; (28) machinery; (29) motor vehicles; (30) transport equipment; (50) water transports; (51) air transports; (58) publishing activities; (59) motion picture, video and television program production, and sound recording and music publishing activities; (60) programming and broadcasting activities; (61) telecommunications; (62) computer programming, consultancy, and related activities; (63) information service activities; (64) financial intermediation; (65) insurance; (66) auxiliary activities to financial intermediation; (69) legal and accounting activities; (70) activities of head offices, management consultancy activities; (71) architectural and engineering activities, technical testing and analysis; (72) scientific research and development; (73) advertising and market research; (74) other professional, scientific, and technical activities; (75) veterinary activities; (78) employment activities; (80) security and investigation activities; (85) education; (86) human health and social work activities; and (90) arts, entertainment and recreation.

[21] The results of the balancing tests are satisfactory for all other propensity scores estimated for the different subsamples of analyzed firms, with bias for all covariates reduced below the 25% critical threshold after matching, and *t*-values for differences in means not significant. Results are available from the authors upon request.

[22] In additional robustness tests available upon request, we also test the validity of our results by performing different matching techniques, applying a Kernel matching with a strict 0.05 bandwidth and using a Kernel-weighted distribution, which downweights the contribution to the outcome of non-treated firms which are further from the propensity score of treated observations within a certain range.

[23] Standard errors are clustered following the Abadie and Imbens (2011) methodology for the nearest-neighbor matching procedure to consider the additional source of variability introduced by the estimation of the propensity score (Heckman and Todd, 1997).

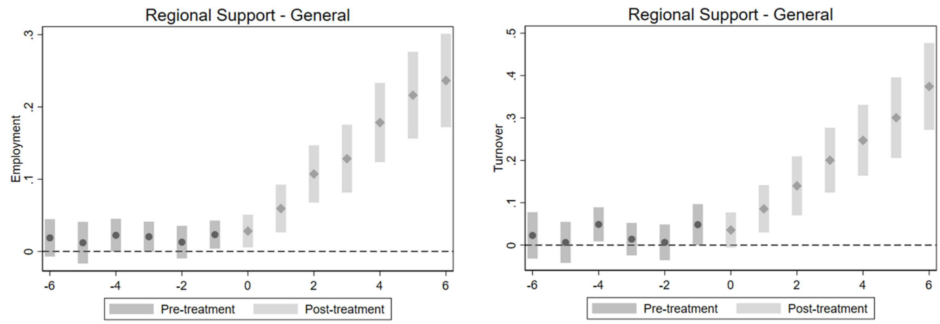

Figure 5. Dynamic impact of regional R&D and innovation support measures on firms' performance. *Note*: Results estimated following the Callaway and Sant'Anna (2021) event study analysis methodology after building a sample of treated and comparable untreated firms using a propensity score nearest-neighbor matching procedure. 95% confidence intervals reported.

and untreated firms over time using a staggered difference-in-differences event study analysis for up to 6 years before and after the treatment (Callaway and Sant'Anna, 2021). This procedure allows us to analyze the dynamic evolution of the treatment over time, differentiating between short- and longer-term effects. In addition, this technique is particularly suitable for dealing with observations treated at different points in time and ensuring that the pretreatment parallel trend assumption is not violated.

6. Results

6.1. Regional support policy

Table 4 reports the estimated results of the direct impact of regional R&D grants on supported firms compared to a comparable group of untreated firms. Regional R&D and innovation grants have substantial and statistically significant impacts on turnover and employment growth, supporting H1. Grant-aided companies grow employment by 21% with respect to comparable untreated firms and grow turnover by 27%. These effects are consistent across industries, with no statistical difference between manufacturing and services firms and nor between high- and low-tech industries. However, these effects are much larger for micro and small firms, in particular, in terms of turnover growth which increases by 27% after being supported, compared to growth of only 6% for larger companies. Figure 5 shows the dynamic evolution of these effects for the general sample of firms.[24] After confirming that there is no statistical difference in the performance of supported and unsupported firms before the treatment, we can see that the impact on employment and turnover increases constantly over time, plateauing 5–6 years after the initial treatment. This evidence suggests longer-term effects of receiving regional R&D support, as it does not result in an immediate step-change in growth, but continuously sustains business growth over a more extended period.

In Table A3, we further distinguish between different types of regional support provided by Invest NI. In this case, we consider only companies funded by Invest NI, considering as "treated" firms supported by R&D grants, while as "untreated" the larger group of comparable firms that have received only innovation vouchers.[25] Overall, we do not identify any significant differences in the performance of firms supported by R&D grants or innovation vouchers. However, we observe substantial industrial heterogeneity in the impact of these two types of regional support, as R&D grants seem to stimulate more employment and turnover growth for services firms in

[24] Results of the event study analysis for all subgroups and additional treatments are consistent with the main results reported and available from the authors upon request.

[25] This, and the next exercise performed for the sectoral support case in Table A4, also helps us to further reduce the threat of a selection bias in our estimation, by focusing only on firms that self-selected into this type of policy support.

Table 4. Impact of regional R&D and innovation support measures on firms' performance

	(1) General	(2) Manufac-turing	(3) Services	(4) High-Tech	(5) Low-Tech	(6) Small	(7) Large
Employment							
Treatment × Post	0.210***	0.205***	0.205***	0.205***	0.208***	0.192***	0.130***
	(0.0104)	(0.0148)	(0.0138)	(0.0200)	(0.0117)	(0.0109)	(0.0319)
Observations	22,239	9176	12,666	6329	16,037	18,724	3621
R-squared	0.944	0.950	0.941	0.944	0.946	0.892	0.898
Turnover							
Treatment × Post	0.276***	0.260***	0.247***	0.288***	0.261***	0.278***	0.0677*
	(0.0147)	(0.0196)	(0.0198)	(0.0293)	(0.0161)	(0.0157)	(0.0398)
Observations	22,239	9176	12,666	6329	16,037	18,724	3621
R-squared	0.941	0.950	0.941	0.935	0.947	0.916	0.909
Control Var.	Y	Y	Y	Y	Y	Y	Y
Firm FE	Y	Y	Y	Y	Y	Y	Y
Year FE	Y	Y	Y	Y	Y	Y	Y
Industry FE	Y	Y	Y	Y	Y	Y	Y

Results estimated using a difference-in-differences model after building a sample of treated and comparable untreated firms using a propensity score nearest-neighbor matching procedure. Bootstrapped Abadie and Imbens (2011) standard errors (*b*, s.e.) are reported in parentheses. The samples are equally divided between treated and control observations.
*$P < 0.10$.
**$P < 0.05$.
***$P < 0.01$.

high-tech industries. At the same time, innovation vouchers are much more effective in supporting the performance of smaller firms operating in low-tech industries.

H2 suggests that as regional support can be more closely tailored to the needs of supported businesses, the growth effects may be greater. To test this, we estimate in Table 5 the difference in performance between Northern Irish firms supported by the regional R&D policy and those supported by national funding provided by UKRI. For employment growth, the effect of regional support is significantly larger than that supported by national measures, providing strong support for H2. In part, this result may reflect the focus of national and subnational schemes on different groups of businesses and the different allocation modes (i.e. competition versus negotiation). We observe that the impact of regional support is significantly different for small firms operating in low-tech services, in terms of both employment and turnover growth, a significant evidence in support of H3a.

We further investigate how subnational R&D and innovation support translate into better firm performance. If the policy measures are well targeted, we expect these employment and turnover growth effects to be mainly driven by an improvement in firms' innovativeness, which allows firms to grow sustainably in the long term. We test this in Table 6, where we consider the impact of subnational R&D and innovation support on the number of patents registered by businesses at the UK IPO. In the top panel of the table, we observe a positive impact of receiving regional R&D and innovation support on the number of registered patents, confirming our hypothesis. This effect is much more substantial for large companies operating in manufacturing and high-tech industries, corresponding to the usual profile of patenting firms. However, given the previous results indicating a larger benefit of regional R&D and innovation support for small- and low-tech service firms, regional support seems to stimulate firms' innovativeness over and beyond the registration of new patents. This could happen through the introduction into the market of new unpatented products and services or via the adoption of new and more efficient technologies into production processes.

6.2. Sectoral support policy

Table 7 reports the estimated impact on growth for firms receiving sectoral support from the Catapult network. These results suggest significant effects of sectoral support on employment and turnover, which increased by 5% and 7%, respectively, relative to untreated firms. This

Table 5. Differential impact on firms' performance of regional support with respect to national UKRI R&D and innovation funding

	(1) General	(2) Manu-facturing	(3) Services	(4) High-tech	(5) Low-tech	(6) Small	(7) Large
Employment							
Treatment × Post	0.398***	0.178	0.405***	0.0285	0.525***	0.371***	0.345
	(0.0608)	(0.321)	(0.0570)	(0.102)	(0.0594)	(0.0650)	(0.395)
Observations	3475	631	2808	1127	2336	2693	330
R-squared	0.936	0.957	0.933	0.949	0.934	0.899	0.913
Turnover							
Treatment × Post	0.212	0.181	0.244*	−0.393	0.569***	0.204	0.193
	(0.153)	(0.1488)	(0.133)	(0.381)	(0.0827)	(0.162)	(0.114)
Observations	3475	631	2808	1127	2336	2693	330
R-squared	0.933	0.957	0.927	0.925	0.940	0.905	0.953
Control Var.	Y	Y	Y	Y	Y	Y	Y
Firm FE	Y	Y	Y	Y	Y	Y	Y
Year FE	Y	Y	Y	Y	Y	Y	Y
Industry FE	Y	Y	Y	Y	Y	Y	Y

Results estimated using a difference-in-differences model after building a sample of treated and comparable untreated firms using a propensity score nearest-neighbor matching procedure. Bootstrapped Abadie and Imbens (2011) standard errors (b, s.e.) are reported in parentheses. The samples are equally divided between treated and control observations.
*$P < 0.10$.
**$P < 0.05$.
***$P < 0.01$.

Table 6. Impact of subnational R&D and innovation support measures on firms' innovativeness

	(1) General	(2) Manufac-turing	(3) Services	(4) High-tech	(5) Low-tech	(6) Small	(7) Large
Regional							
Treatment × Post	0.00551***	0.00857***	0.00197**	0.00799***	0.00351***	0.00243***	0.0125**
	(0.00121)	(0.00252)	(0.000916)	(0.00291)	(0.00113)	(0.000787)	(0.00603)
Observations	22,239	9072	12,786	6445	15,750	18,067	4118
R-squared	0.186	0.216	0.153	0.200	0.208	0.130	0.266
Sectoral							
Treatment × Post	0.0353***	0.0381***	0.0236***	0.0462***	0.0185**	0.0529***	0.00668
	(0.00614)	(0.00780)	(0.00838)	(0.00848)	(0.00885)	(0.00729)	(0.00778)
Observations	40,812	14,541	26,082	22,449	18,243	23,493	17,180
R-squared	0.983	0.986	0.982	0.983	0.985	0.934	0.982
Control Var.	Y	Y	Y	Y	Y	Y	Y
Firm FE	Y	Y	Y	Y	Y	Y	Y
Year FE	Y	Y	Y	Y	Y	Y	Y
Industry FE	Y	Y	Y	Y	Y	Y	Y

Results estimated using a difference-in-differences model after building a sample of treated and comparable untreated firms using a propensity score nearest-neighbor matching procedure. Bootstrapped Abadie and Imbens (2011) standard errors (b, s.e.) are reported in parentheses. The samples are equally divided between treated and control observations. The dependent variable is the log number of patents registered by firms at the UK IPO in each year.
*$P < 0.10$.
**$P < 0.05$.
***$P < 0.01$.

again provides support for H1 in the case of sectoral support. However, these are significantly

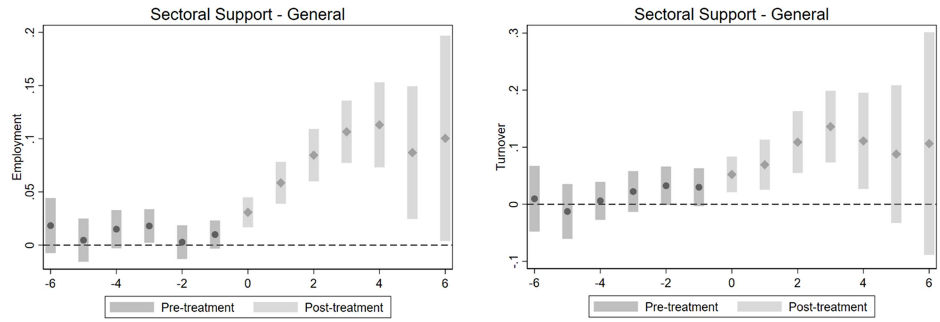

Figure 6. Dynamic impact of sectoral R&D and innovation support measures on firms' performance. *Note*: Results estimated following the Callaway and Sant'Anna (2021) event study analysis methodology after building a sample of treated and comparable untreated firms using a propensity score nearest-neighbor matching procedure. 95% confidence intervals reported.

Table 7. Impact of sectoral R&D and innovation support measures on firms' performance

	(1) General	(2) Manufacturing	(3) Services	(4) High-tech	(5) Low-tech	(6) Small	(7) Large
Employment							
Treatment × Post	0.0500***	0.0355***	0.0250***	0.0377***	0.0795***	0.0242***	0.0327***
	(0.00607)	(0.00825)	(0.00821)	(0.00869)	(0.00889)	(0.00770)	(0.00904)
Observations	41,108	14,846	26,275	22,977	18,063	23,680	17,454
R-squared	0.983	0.982	0.983	0.980	0.985	0.925	0.973
Turnover							
Treatment × Post	0.0749***	0.0341***	0.0637***	0.0640***	0.0742***	0.0322**	0.0329**
	(0.0104)	(0.0118)	(0.0150)	(0.0159)	(0.0138)	(0.0146)	(0.0145)
Observations	41,108	14,846	26,275	22,977	18,063	23,680	17,454
R-squared	0.971	0.976	0.969	0.966	0.975	0.927	0.962
Control Var.	Y	Y	Y	Y	Y	Y	Y
Firm FE	Y	Y	Y	Y	Y	Y	Y
Year FE	Y	Y	Y	Y	Y	Y	Y
Industry FE	Y	Y	Y	Y	Y	Y	Y

Results estimated using a difference-in-differences model after building a sample of treated and comparable untreated firms using a propensity score nearest-neighbor matching procedure. Bootstrapped Abadie and Imbens (2011) standard errors (*b*, s.e.) reported in parentheses. The samples are equally divided between treated and control observations.
***$P < 0.01$.
**$P < 0.05$.
*$P < 0.10$.

smaller than the effects estimated for regional support. This could be explained by the fact that Catapults does not dispense financial support but only assists businesses by providing access to R&D infrastructures and by linking businesses with academic scientists, technical specialists, and research experts to stimulate collaborations and knowledge exchange. We do not observe any significant industrial heterogeneity in the impact of sectoral support, except for stronger employment growth for low-tech firms. Figure 6 shows a similar dynamic pattern of these effects to those estimated for regional support, with a gradual but steady increase in employment and turnover over time. These effects, however, seem to fade away 4–5 years after the sectoral support started, earlier than in the case of regional support. This could again be explained by the different types of treatments or simply by the fact that sectoral support is mostly concentrated in the later years in our sample, and thus, we might not have sufficient observations to precisely estimate the longer-term effects, as hinted by the large confidence intervals for the later years.

Table 8. Differential impact on firms' performance of sectoral support with respect to national UKRI R&D and innovation funding

	(1) General	(2) Manufacturing	(3) Services	(4) High-tech	(5) Low-tech	(6) Small	(7) Large
Employment							
Treatment × Post	0.0200**	0.0203*	0.0161	0.0278**	0.0370***	−0.0101	0.0478***
	(0.00811)	(0.0106)	(0.0107)	(0.0118)	(0.0109)	(0.00959)	(0.0129)
Observations	24,738	8851	15,979	12,938	11,767	15,904	9066
R-squared	0.978	0.976	0.979	0.977	0.979	0.923	0.961
Turnover							
Treatment × Post	0.00713	−0.0114	0.0195	0.0257	0.0243	−0.00279	0.0310
	(0.0141)	(0.0152)	(0.0180)	(0.0215)	(0.0174)	(0.0167)	(0.0237)
Observations	24,738	8851	15,979	12,938	11,767	15,904	9066
R-squared	0.965	0.968	0.967	0.961	0.969	0.929	0.945
Control Var.	Y	Y	Y	Y	Y	Y	Y
Firm FE	Y	Y	Y	Y	Y	Y	Y
Year FE	Y	Y	Y	Y	Y	Y	Y
Industry FE	Y	Y	Y	Y	Y	Y	Y

Results estimated using a difference-in-differences model after building a sample of treated and comparable untreated firms using a propensity score nearest-neighbor matching procedure. Bootstrapped Abadie and Imbens (2011) standard errors (*b*, s.e.) are reported in parentheses. The samples are equally divided between treated and control observations.
*$P < 0.10$.
**$P < 0.05$.
***$P < 0.01$.

In Table A4, we further distinguish between different types of sectoral support provided by the Catapults networks, particularly differentiating between medium- to high- and low-intensity engagements. Catapults classify all engagements into these two categories, where low-intensity mainly results in a request for information from businesses, while medium–high intensity involves some type of collaboration with the Catapults. In this analysis, we consider only companies that engaged with Catapults, which are included as "treated" firms with medium- to high-intensity engagement, while including in as "untreated" the larger group of firms with only low levels of engagement. The positive effect of sectoral support seems to be driven entirely by medium to high-intensity engagements, where firms are engaged in a knowledge exchange with Catapults. This is further evidence that we are estimating the effect of policy support rather than simply the self-selection of larger and more productive firms into these treatments.

Considering H2 for sectoral support, i.e. that sectoral supports should have stronger growth impacts than national support measures, in Table 8, we find supportive evidence only regarding employment growth. In this case, we also observe significant industrial heterogeneity, as the differential impact with respect to national support is felt only by large firms in the manufacturing industry. These differences could also be related to the impact of sectoral support on firms' innovativeness, which is analyzed in the bottom panel of Table 6. First of all, we observe that the impact of sectoral support on firms' patenting activity is much stronger than that in the case of regional support. Second, the estimated effect is particularly significant for firms in high-tech manufacturing sectors. This can be explained by the mission of Catapults as technology and innovation centers to foster the creation of marketable inventions and by their strategy of targeting high-value manufacturing. This can also explain the stronger effect of sectoral support compared to national support for manufacturing companies, thus providing further evidence supporting H3a.

Table 9. Differential impact on firms' performance of national UKRI support with or without regional R&D and innovation funding

	(1) General	(2) Manufacturing	(3) Services	(4) High-tech	(5) Low-tech	(6) Small	(7) Large
Employment							
Treatment × Post	0.353***	0.379**	0.231	0.411***	0.204	0.417***	−0.0301
	(0.104)	(0.162)	(0.14)	(0.12)	(0.176)	(0.134)	(0.0687)
Observations	515	271	243	285	229	284	230
R-squared	0.983	0.988	0.968	0.984	0.982	0.938	0.994
Turnover							
Treatment × Post	0.0244	0.387*	−0.205	0.0953	0.294	0.0936***	−0.248
	(0.185)	(0.203)	(0.29)	(0.237)	(0.281)	(0.026)	(0.197)
Observations	515	271	243	285	229	284	230
R-squared	0.974	0.981	0.956	0.967	0.979	0.932	0.987
Control Var.	Y	Y	Y	Y	Y	Y	Y
Firm FE	Y	Y	Y	Y	Y	Y	Y
Year FE	Y	Y	Y	Y	Y	Y	Y
Industry FE	Y	Y	Y	Y	Y	Y	Y

Results estimated using a difference-in-differences model after building a sample of treated and comparable untreated firms using a propensity score nearest-neighbor matching procedure. Bootstrapped Abadie and Imbens (2011) standard errors (b, s.e.) are reported in parentheses. The samples are equally divided between treated and control observations.
*$P < 0.10$.
**$P < 0.05$.
***$P < 0.01$.

6.3. Complementarities in national and subnational R&D public support

We focus further on the potential complementarities between R&D support policies at different levels (Hypotheses 3b and 3c). First, we try to understand whether there are static complementarities between subnational support and national research funding (Douglas and Radicic, 2020), i.e. whether subnational support increases the economic benefit that firms derive from national support (H3b). Table 9 presents the results of this analysis for regional support, where we compare the performance of businesses that received a national-level UKRI grant in combination with the support of regional funding. We find additional positive effects of regional support on top of national financing for employment growth. Small firms in manufacturing sectors mostly drive this effect, while no significant additionality is estimated across other groups. Table 10 reports a similar analysis for sectoral support, where we compare the performance of businesses that received a national-level UKRI grant with or without the sector-specific support of a Catapult. Similar to the evidence for the regional support, we find evidence of additionality for firms involved in UKRI-funded R&D projects with the partnership of a Catapult. Also, in this case, there is a marked industrial heterogeneity, with additional benefits from the complementarity of national and sectoral support mainly for small businesses operating in high-tech manufacturing industries. This provides consistent evidence for static complementarities between subnational and national support measures (H3b).

Finally, we explore the potential for dynamic complementarities between subnational and national R&D public support schemes by analyzing in Table 11 whether the support of Invest NI or of the Catapult network helps companies to apply for and successfully secure national R&D grants (H3c). To estimate this, we consider as treated firms those that have received subnational support, while the control group consists of comparable firms that have never received subnational support and have not previously received national R&D support from UKRI. Our findings corroborate only partially support H3c, as we identify strong evidence of dynamic complementarities only for the sectoral support, as in general, engaging with Catapults increases the likelihood of securing UKRI funding in the following years by 2.5% more than in comparable untreated firms. This is particularly the case for high-tech and medium-large firms, thus mostly benefiting the segment of the business population that is more likely to receive the support of

Table 10. Differential impact on firms' performance of national UKRI support with or without sectoral R&D and innovation funding

	(1) General	(2) Manufacturing	(3) Services	(4) High-tech	(5) Low-tech	(6) Small	(7) Large
Employment							
Treatment × Post	0.00461	0.0232	0.000491	0.0368**	−0.0174	0.00845	0.0190
	(0.0161)	(0.0206)	(0.0215)	(0.0148)	(0.0206)	(0.0253)	(0.0165)
Observations	9767	3546	6140	5907	3824	3989	5738
R-squared	0.987	0.989	0.987	0.984	0.992	0.913	0.987
Turnover							
Treatment × Post	0.0515*	0.0939***	0.0258	0.0561**	0.0328	0.125**	−0.0128
	(0.0308)	(0.0331)	(0.0437)	(0.0239)	(0.0366)	(0.0553)	(0.0353)
Observations	9767	3546	6140	5907	3824	3989	5738
R-squared	0.977	0.985	0.976	0.972	0.987	0.933	0.972
Control Var.	Y	Y	Y	Y	Y	Y	Y
Firm FE	Y	Y	Y	Y	Y	Y	Y
Year FE	Y	Y	Y	Y	Y	Y	Y
Industry FE	Y	Y	Y	Y	Y	Y	Y

Results estimated using a difference-in-differences model after building a sample of treated and comparable untreated firms using a propensity score nearest-neighbor matching procedure. Bootstrapped Abadie and Imbens (2011) standard errors (*b*, s.e.) are reported in parentheses. The samples are equally divided between treated and control observations.
$^{*}P < 0.10$.
$^{**}P < 0.05$.
$^{***}P < 0.01$.

national-level UKRI funding. This is additional evidence favoring the dynamic complementarities envisaged by Douglas and Radicic (2020). We do not find higher probabilities of securing national UKRI funding for firms previously supported by regional Invest NI schemes, except for large companies (+1%). These differences between the two subnational schemes could be explained by their different coverage. While regional support is spread across all sectors, the sectoral support of Catapults is quite focused on specific high-tech sectors, thus promoting innovation among a group of firms more in line with the type of research and innovation supported by the national UKRI funding.

7. Discussion and conclusions

Public support for R&D and innovation can be critical for addressing systemic failures that hinder national, regional, and sectoral innovation systems (OECD, 1999; Woolthuis *et al*., 2005). However, relatively little is known about the potential trade-offs and complementarities between subnational and national innovation policy—the multilevel policy mix (Magro and Wilson, 2013, 2019; Anderton, 2017)—and their effect on business innovativeness and performance. Here, we examine the comparative benefits of regional, sectoral, and national R&D and innovation policy support in the UK and their potential complementarities. Regarding regional support, we consider the growth benefits of R&D and innovation support measures provided by Invest NI, the economic development agency for NI. The UK Catapult network provides sectoral support measures.

We make three main findings. First, we find that regional, sectoral, and national support measures tend to focus on different elements of the business population, which is reflected in the impacts and complementarities of the policy programs. In the UK at least, regional support measures focus predominantly on smaller firms, often in services and low-tech sectors, while

Table 11. Impact of subnational R&D and innovation support measures on firms' likelihood of receiving national UKRI R&D and innovation funding

	(1) General	(2) Manufacturing	(3) Services	(4) High-tech	(5) Low-tech	(6) Small	(7) Large
Regional Treatment × Post	0.000526	0.000214	0.000385	0.00331	−0.000985	−0.00130	0.0104*
	(0.00140)	(0.00274)	(0.00147)	(0.00357)	(0.00145)	(0.00116)	(0.00567)
Observations	30,268	11,737	17,666	8114	22,142	25,637	4608
R-squared	0.420	0.402	0.471	0.477	0.374	0.418	0.397
Sectoral Treatment × Post	0.0244***	0.0195**	0.0178**	0.0349***	0.0211***	0.00874	0.0373***
	(0.00554)	(0.00916)	(0.00736)	(0.00837)	(0.00732)	(0.00707)	(0.00917)
Observations	28,030	10,328	17,502	15,391	12,480	15,699	12,042
R-squared	0.778	0.774	0.777	0.774	0.777	0.726	0.805
Control Var.	Y	Y	Y	Y	Y	Y	Y
Firm FE	Y	Y	Y	Y	Y	Y	Y
Year FE	Y	Y	Y	Y	Y	Y	Y
Industry FE	Y	Y	Y	Y	Y	Y	Y

Results estimated using a difference-in-differences model after building a sample of treated and comparable untreated firms using a propensity score nearest-neighbor matching procedure. Bootstrapped Abadie and Imbens (2011) standard errors (b, s.e.) are reported in parentheses. The samples are equally divided between treated and control observations. The dependent variable is a dummy variable equal to 1 if the company has received national UKRI R&D and innovation funding for the first time or 0 otherwise.
*$P < 0.10$.
**$P < 0.05$.
***$P < 0.01$.

sectoral support measures also focus on smaller firms, but with particular focus on high-tech manufacturing industries. The UK national support for innovation and R&D focuses on larger, high-tech companies. Second, regional and sectoral support measures have positive benefits for employment, turnover, and patenting growth, reflecting other evidence of the additionality of direct R&D and innovation supports (Zuniga-Vicente *et al.*, 2014). Overall, regional support measures generate significantly higher growth benefits for participating firms than national or sectoral schemes compared to closely matched control groups, i.e. even allowing for their differential focus. This may reflect the types of firms that are being supported: regional schemes support smaller firms where additionality is often found to be stronger (Becker *et al.*, 2017; Cunningham *et al.*, 2016). However, it may also reflect the different allocation approaches used in regional and national support measures in the UK: regional supports are largely negotiated with, and therefore tailored to, individual firms, while national support measures are delivered through open competitions. This type of negotiated support mechanism may be particularly important for smaller firms, which may struggle with the formal application process, and fixed costs, involved in applying to national grant competitions.

Third, we consider potential static and dynamic complementarities between regional, sectoral, and national support measures (Douglas and Radicic, 2020). We find strong evidence of static complementarities between subnational and national support measures, as the performance benefits of national support measures are much higher with the joint support of regional or sectoral policies, particularly for small manufacturing firms. In addition, there are strong dynamic complementarities between subnational and national R&D and innovation support, but only in the case of sectoral support, as firms supported by Catapults are more likely to obtain national support over the following years. This suggests the importance of complementary mechanisms for advantaging firms that have received subnational support in subsequent national competitions.

These may relate to cumulated knowledge, signaling effects associated with the award of previous support or learning around application processes. In either case, the performance benefits for firms combining subnational and later national support measures will likely be reinforcing.

Notably, these dynamic complementarities are strongest where recipient firms are either larger or in high-tech sectors, a finding that applies to both regional and sectoral support. These firms' resource advantages—and perhaps technical sophistication—enable them to capitalize most effectively on subnational support in subsequent competitions for national R&D and innovation support. Given the positive innovation and growth benefits of national support measures (Scandura, 2006; Vanino *et al*., 2019), this pattern of dynamic complementarities is likely to exacerbate performance differences between smaller and larger firms. However, it may also reduce the mean additionality of national support measures, which typically achieve stronger additionality among smaller firms (Vanino *et al*., 2019).

Our findings suggest that complementarities can arise in a multilevel policy mix, with complementarity between regional, sectoral, and national support measures. Targeting complementarities can occur where different levels of policy intervention focus on different types of companies: smaller firms in the regional and sectoral support measures and larger firms at the national level. This may reflect the life cycle or development trajectory of firms themselves: start-up or smaller companies may be more likely to seek "local" support—either sectoral or regional, depending on their technological intensity—before graduating toward national awards as their technological capabilities and innovation competencies improve. This is also reflected in the importance of dynamic complementarities. For larger firms in NI, for example, local R&D and innovation support measures, delivered through the negotiated Invest NI model, provide a stepping-stone to more competitive national R&D and innovation support. Similarly, collaborative support derived from the Catapults may also strengthen their capability to be successful in national funding competitions.

As indicated earlier, the support regimes for R&D and innovation in different parts of the UK differ markedly, with firms in Scotland, Wales, and NI having access to regional support measures and national support from UKRI. This suggests the potential for dynamic complementarities between regional and national support measures in each devolved territory. By contrast, the recent development of the R&D and innovation support system in England may actually have acted to reduce any regional–national dynamic complementarities. As of 2008–2010, regional R&D and innovation support was available for small firms across English regions through the RDAs, alongside national support from the forerunners of UKRI and Innovate UK. This tier of support measures was removed, along with any dynamic complementarities it created, in 2012, when the RDAs were closed down. Moving back toward more regionalized support for R&D and innovation in England over the past years as part of the devolution agenda (e.g. Launchpads and Innovation Accelerators) may re-create the potential for dynamic complementarities between regional and national support in England. It is notable, however, that these recent localized support schemes have been competition-based rather than providing negotiated support packages of the type examined here. Alongside these spatial changes, the Catapult network and other sectoral intermediaries have expanded and developed across the UK over the last decade. This will likely strengthen sectoral–national dynamic complementarities as firms benefit from sectorally oriented support measures before seeking national R&D or innovation funding.

Our analysis clearly illustrates the potential for both targeted and dynamic complementarities to increase the value of public support for R&D and innovation. However, maximizing the effects of such complementarities would require an element of coordination between system actors at different levels. At a national level in the UK, the establishment of UKRI in 2018 provides a coordinating framework for national support provided by the UK's Research Councils, including Innovate UK. Increasing devolved decision-making and governance would require more efficient mechanisms to coordinate national and regional R&D and innovation support, or the support delivered by many sectoral intermediaries. From a different perspective, our current understanding of firms' "customer journey" through the UK's R&D and innovation support system is minimal (Ong *et al*., 2022). How, and why, dynamic complementarities arise remains unclear. Do sectoral support recipients improve their technological or commercial capabilities, and so improve their access to national schemes? Or, is this simply about a better understanding of the grants system? Or firms' ability to formulate a more compelling project proposal? Future studies could usefully adopt a customer journey lens to examine the learning mechanisms that underpin the dynamic complementarities we identify.

Other limitations to our study are also evident. First, here, we consider only two specific sources of subnational funding for R&D and innovation. Care is necessary for generalizing our results to other subnational policy interventions, which may have very different target groups, intervention profiles, and decision rules. Future work could usefully extend to other subnational interventions and extend the geographical focus of the study beyond the UK. Second, data limitations mean that we focus here on particular measures of firm performance as our outcome variables. Broadening this to look at indicators related to productivity, sustainability, or other measures of innovativeness may provide a different perspective on both the impact and complementarity of R&D and innovation support measures. Finally, our study is based on a PSM approach combined with a difference-in-differences methodology, which is subject to a range of limitations linked principally to self-selection and the potential impact of the unobservable characteristics of firms (Reiffel, 2020). Future analysis using administrative data also on unsuccessful applications, or based on survey data where attitudinal and behavioral information is included, may be a useful extension to improve the robustness of our analysis further.

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Table A1. Propensity score estimation and balancing test for matched observations in the analysis of receiving regional support from Invest NI

Regional balancing test	Coefficient	T-value	Treated	Control	Mean bias	Bias reduction	T-value	P-value	$V(T)/V(C)$
L. Employment	0.4087792	23.13	2.7719	2.7382	3.2	96.9	0.5	0.615	0.71
L. Productivity	0.1332896	7.45	4.4634	4.4441	1.8	97.3	0.41	0.682	0.8
L. Patents Stock	−0.027695	0.15	0.00523	0	7.8	41.1	1.34	0.181	0.95
Employment Growth	0.1626634	4.86	0.14409	0.14087	0.7	97.9	0.13	0.897	0.88
Productivity Growth	0.0697461	3.46	0.13723	0.19911	7.5	35.4	1.5	0.134	0.65
Age	−0.2352246	8.44	2.7682	2.7209	4.8	87.9	1.51	0.131	1.06
Group	−0.0501429	1.03	0.22181	0.23296	3.7	89.1	0.53	0.593	-
Foreign	−0.1517995	1.92	0.07187	0.07559	2.3	88.3	0.29	0.775	-
Single Plant	−0.48543	5.61	0.01983	0.02602	1.5	98.2	0.83	0.406	-
Agglomeration	0.0187597	2.05	1.703	1.8215	7.6	55.8	1.04	0.299	0.51
Entry Rate	−0.219535	0.3	0.00824	0.00895	2.2	88	0.6	0.55	1.61
Reg-Ind Productivity	−0.0727272	2.1	4.584	4.5617	3.3	93	0.71	0.476	0.84
Reg-Ind Employment	−0.0657183	4.36	6.0802	6.13	2.9	94.1	0.6	0.55	0.85
Market Share	−0.2224345	2.27	0.16016	0.15434	3.1	94.4	0.45	0.651	1.05
Reg-Ind R&D Grants	0.0283004	8.12	4.1561	4.5056	4.2	92.9	0.77	0.444	0.43
	No. of observations	R-sq	PS R-sq	LR Chi-sq	P-value	Mean bias	Median bias	B	R
	258,791	0.2853	0.004	8.25	0.876	3.8	3.2	14.3	0.79

Propensity score estimation and matching balancing test reported in this table refer to the results shown in Column 1 of Table 4 (receiving regional support versus no support for the general sample of firms). Estimations and tests for the other analysis are similar and consistent and are available upon request. The second and third columns report the results of the propensity score estimation using a probit model. Robust standard errors reported in parentheses. Columns 4 and 5 present the mean value of each control variable for firms in the treated and control groups after the implementation of the matching technique. In Column 6, we display the median standard bias across all the covariates included in the logit estimation after the matching procedure. Columns 7 and 8 report the t-tests for the equality of the mean values between treated and untreated firms in the matched sample. Column 9 shows the ratio of variance of residuals orthogonal to the linear index of the propensity score in the treated group. The bottom row presents a summary of statistics regarding the whole sample: the pseudo R^2 from the probit estimation and the corresponding χ^2 statistic and P-value of likelihood-ratio test of joint significance of covariates; the mean and median bias as summary indicators of the distribution of bias across the samples; Rubin's B shows the absolute standardized difference in means of linear index of propensity score in treated and matched non-treated groups, while Rubin's R is the ratio of treated to matched non-treated variances of the propensity score index. Finally, the total number of treated and control observations in the support sample is included.

Table A2. Propensity score estimation and balancing test for matched observations in the analysis receiving sectoral support from Catapults

Sectoral balancing test	Coefficients	*T*-value	Treated	Control	Mean bias	Bias reduction	*T*-value	*P*-value	*V*(*T*)/*V*(*C*)
L. Employment	0.2750204	39.42	3.7742	3.8268	3.5	96.5	0.91	0.362	1.04
L. Productivity	0.0274344	3.6	4.5791	4.5843	0.4	98.7	0.15	0.88	1.23
L. Patents Stock	0.1818933	12.85	0.21216	0.24245	6.7	72.8	1.1	0.271	0.80
Employment Growth	0.0881821	6.99	0.22909	0.24479	3	88	0.88	0.379	0.66
Productivity Growth	0.0336151	4.07	0.09671	0.08963	0.8	86.6	0.27	0.788	1.02
Age	−0.0540812	3.59	2.949	2.9384	1.2	95.2	0.56	0.574	1.03
Group	0.1914433	10.25	0.57191	0.58979	4.4	95.6	1.24	0.214	-
Foreign	−0.0225883	0.95	0.19191	0.2017	3.6	93.1	0.84	0.399	-
Single Plant	0.0382305	1.86	0.27149	0.25957	2.4	94.4	0.92	0.355	-
Agglomeration	0.0001141	0.13	2.9613	2.7743	2.5	75	0.79	0.432	1.50
Entry Rate	−0.4736436	1.18	0.01363	0.01346	0.7	86.4	0.28	0.783	1.12
Reg-Ind Productivity	−0.0324869	2.08	4.7534	4.7602	0.9	97.2	0.34	0.733	0.98
Reg-Ind Employment	0.0023561	0.48	7.6183	7.6778	2.8	5653.2	0.98	0.326	0.91
Market Share	−0.0539493	1.29	0.17903	0.17578	1.6	97.1	0.37	0.709	1.02
	No. of observations	*R*-sq	PS *R*-sq	LR Chi-sq	*P*-value	Mean bias	Median bias	*B*	*R*
	6,040,597	0.29	0.001	8.05	0.887	2.5	2.5	8.3	0.9

Propensity score estimation and matching balancing test reported in this table refer to the results shown in Column 1 of Table 7 (engagement with Catapults versus no engagement for the general sample of firms). Estimations and tests for the other analysis are similar and consistent and are available upon request. The second and third columns report the results of the propensity score estimation using a probit model. Robust standard errors reported in parentheses. Columns 4 and 5 present the mean value of each control variable for firms in the treated and control groups after the implementation of the matching technique. In Column 6, we display the median standard bias across all the covariates included in the logit estimation after the matching procedure. Columns 7 and 8 report the *t*-tests for the equality of the mean values between treated and untreated firms in the matched sample. Column 9 shows the ratio of variance of residuals orthogonal to the linear index of the propensity score in the treated group. The bottom row presents a summary of statistics regarding the whole sample: the pseudo R^2 from the probit estimation and the corresponding χ^2 statistic and *P*-value of likelihood-ratio test of joint significance of covariates; the mean and median bias as summary indicators of the distribution of bias across the samples; Rubin's *B* shows the absolute standardized difference in means of linear index of propensity score in treated and matched non-treated groups, while Rubin's *R* is the ratio of treated to matched non-treated variances of the propensity score index. Finally, the total number of treated and control observations in the support sample is included.

Table A3. Differential impact of regional R&D grants and innovation vouchers on firms' performance

	(1) General	(2) Manufacturing	(3) Services	(4) High-tech	(5) Low-tech	(6) Small	(7) Large
Employment							
Treatment × Post	0.0369*	−0.000910	0.0559*	0.0830**	−0.0572**	0.00460	0.0260
	(0.0201)	(0.0269)	(0.0308)	(0.0355)	(0.0245)	(0.0224)	(0.0421)
Observations	6600	3516	3078	2658	3946	5089	1317
R-squared	0.949	0.951	0.945	0.946	0.953	0.901	0.938
Turnover							
Treatment × Post	0.000968	−0.0172	0.102**	0.0899*	−0.101***	−0.0564*	0.00150
	(0.0285)	(0.0352)	(0.0438)	(0.0524)	(0.0334)	(0.0340)	(0.0480)
Observations	6600	3516	3078	2658	3946	5089	1317
R-squared	0.946	0.949	0.943	0.941	0.950	0.913	0.944
Control Var.	Y	Y	Y	Y	Y	Y	Y
Firm FE	Y	Y	Y	Y	Y	Y	Y
Year FE	Y	Y	Y	Y	Y	Y	Y
Industry FE	Y	Y	Y	Y	Y	Y	Y

Results estimated using a difference-in-differences model after building a sample of treated and comparable untreated firms using a propensity score nearest-neighbor matching procedure. Bootstrapped Abadie and Imbens (2011) standard errors (b, s.e.) are reported in parentheses. The samples are equally divided between treated and control observations.
*$P < 0.10$.
**$P < 0.05$.
***$P < 0.01$.

Table A4. Differential impact of high- and low-intensity sectoral R&D and innovation support on firms' performance

	(1) General	(2) Manufacturing	(3) Services	(4) High-tech	(5) Low-tech	(6) Small	(7) Large
Employment							
Treatment × Post	0.0346***	0.0299*	0.0537***	0.0256*	0.0190	0.0533***	0.0448***
	(0.0108)	(0.0153)	(0.0133)	(0.0135)	(0.0146)	(0.0135)	(0.0166)
Observations	15,841	6989	9087	8740	7536	9103	7113
R-squared	0.985	0.984	0.987	0.987	0.985	0.926	0.981
Turnover							
Treatment × Post	0.0733***	0.0259	0.0986***	0.112***	0.0160	0.127***	0.125***
	(0.0208)	(0.0258)	(0.0253)	(0.0277)	(0.0248)	(0.0272)	(0.0293)
Observations	15,841	6989	9087	8740	7536	9103	7113
R-squared	0.968	0.978	0.970	0.966	0.978	0.916	0.967
Control Var.	Y	Y	Y	Y	Y	Y	Y
Firm FE	Y	Y	Y	Y	Y	Y	Y
Year FE	Y	Y	Y	Y	Y	Y	Y
Industry FE	Y	Y	Y	Y	Y	Y	Y

Results estimated with a difference-in-difference model after building a sample of treated and comparable untreated firms using a propensity score nearest-neighbor matching procedure. Bootstrapped Abadie and Imbens (2011) standard errors (b, s.e.) reported in parentheses. The samples are equally divided between treated and control observations.
*$P < 0.10$.
**$P < 0.05$.
***$P < 0.01$.

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