Do UK Research and Collaborations in R&I Promote Economic Prosperity and Levelling-up?

An analysis of UKRI funding between 2004-2021

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Abstract

We analyse the impact of public funding on research-related investments in the UK and its contribution to regional development and interregional convergence. Our novel methodology, using multilevel-mediation modelling and social network analysis techniques, enables us to identify complex effects within and between regions, resulting from UK Government R&D public support during the period 2004-2021. We demonstrate that publicly-supported R&D leverages private R&D as intended. However, the effects on regional economic development and convergence depend crucially on the levels and forms of regional collaboration designed in the programmes. These insights have not before been empirically demonstrated in such a robust manner.

1. Introduction

The aim of this paper is to investigate the ways in which location-specific publicly-funded research and development (R&D) and research and innovation (R&I) funding may contribute to regional economic development. In particular, in the UK context, we investigate the role which location-specific publicly-funded R&I has contributed either to the narrowing and convergence of regional productivity divides, typically referred to as 'Levelling Up' in UK political economy arenas, or alternatively, to the widening and divergence of UK regional productivity divides. The backdrop to these discussions is that the UK Government unveiled its Levelling Up White Paper in 2022 (HM Government, 2022a). The White Paper aims to tackle the issue of economic and governance centralisation in the country and the unequal economic outcomes observed across the regions in recent years (Martin et al., 2022; McCann, 2016). To rebalance the national economy, the White Paper outlines twelve main 'missions', of which a key part is a focus on the role played by science, technology, and education (HM Government, 2022b). One of these core missions aims to increase public investment in Research and Development outside of the South East by 40% by 2030, thereby expanding location-specific publicly-funded R&I to the Midlands, Northern and Celtic regions, with the intention of fostering interregional convergence by encouraging private sector investment to drive innovation and productivity growth in these regions (HM Government, 2022b). Yet, whether these spatial shifts in R&D and R&I funding might help to spatially rebalance the economy depends on how publicly-funded R&D helps to shape regional development and convergence.

In order to illustrate the role played by public R&I funding in shaping regional development and convergence or 'Levelling Up', in this paper, we develop a novel methodology for capturing the indirect and induced effects of public R&I schemes by using social network analysis techniques, which are framed in a manner that allows us to construct a novel panel data for multilevel mediation analysis. This technique then allows us to analyse not only the distribution of partnerships but also to categorise and measure the strength of R&I relationships across almost two decades of UK publicly-funded R&I schemes. In particular, our technique allows us to uncover all of the direct, indirect and induced development effects operating both within and between regions, arising as a result of public funding.

Our empirical analysis exploits the UK Research and Innovation (UKRI) repository of funded projects between 2004 and May 2021. These UKRI support programs account for some 32% of total UK Government R&D publicly support funding. This information is complemented with data from the ONS (Office for National Statistics) and by the web-scraping of data and information on individual firms from the Companies House website. Our dataset contains 25,122 projects and 44,406 participant firms and organisations, and we extract information on all collaborative research and development (R&D) activities, feasibility activities, smart and innovation voucher grants, and all Knowledge Transfer Partnerships in 41 UK NUTS2 (ITL2) regions over 18 years.

By linking these R&I project data to spatial data via our novel methodology for capturing the indirect and induced effects of public R&I schemes based on multilevel structural equation modelling, we are able to empirically test how different types of publicly-funded R&D and R&I collaborations may directly or indirectly affect regional economic development and economic convergence processes. In particular, we explore the potential mediating role of gross expenditure on research and development (BERD) using a novel multilevel structural equation modelling that allows for mediation treatments.

Our results support the argument that knowledge collaborations have a positive effect on regional economic prosperity, and this effect is mediated by the effect of regional business R&D. Interregional collaboration appears to be the main contributor to economic prosperity over other types of regional collaborations. However, in the case of the UK, our results fail to find any support for the indirect relationship between publicly funded R&D and collaboration on regional economic convergence. Indeed, if anything, the highly concentrated geography of public R&I funding in the UK's most prosperous regions has helped to foster further regional divergence. These findings, therefore, allow us to consider the conditions under which publicly-funded R&D and R&I investments may be used to foster regional convergence.

The rest of the paper is structured as follows. The next section outlines the key literature which underpins the main hypotheses articulating the relationships between R&D, R&D collaboration and economic development and regional convergence, as well as the mediation effect of regional business R&D. Section 3 presents the dataset, sample and main variables for the analysis. Section 4 explains the novel methodology we employ, which is a multilevel mediation panel data model, a technique which allows us to uncover all of the direct, indirect and induced development effects operating both within and between regions, arising as a result of the public funding. Section 5 provides the results and also a discussion of our results, while section 6 provides a further discussion and some brief conclusions.

2. Theoretical background: R&D investments and economic growth

The positive impact of R&D on economic growth has been the basis of many theoretical contributions and subsequent empirical work at different levels of analysis (see, inter alia, Arrow, 1962; Romer, 1986, 1990; Grossman and Helpman, 1991; Aghion and Howitt, 1998; Proudman and Redding, 1998; for the theory and, inter alia, Cameron, Proudman and Redding, 2005; Kafouros, 2005; Coe, Helpman and Hoffmeister, 2009; O'Mahony and Vecchi, 2009; Bravo-Ortega and Marin, 2011; Becker, 2015; Celli et al., 2021). Knowledge accumulation and its spillovers are recognised as important determinants of innovation performance and economic growth (Jaffe, 1989; Romer, 1986) and firm productivity (Ortega-Argiles et al., 2011, 2014, 2015; Audretsch and Belitski, 2020). There has been a long tradition aimed at identifying knowledge spillovers and externalities at the sectoral and national levels (Malerba 2004; Acemoglu et al. 2016), and while some early papers argued that public subsidies to R&D may crowd out private R&D, increasingly over time the more recent literature has shifted away from the earlier arguments to finding that public subsidies typically stimulate private R&D, although this is not always the case (Crescenzi et al., 2018).

In this context, public policies are typically considered within three main categories: R&D tax credits and direct subsidies, support of the university research system and the formation of high-skilled human capital, and support of formal R&D cooperations across various institutions (Becker, 2015). Subsidizing R&D investment has been a widespread policy in many countries over the past thirty to fifty years. Tax credits are widely found to have positive effects on R&D. Similarly, university research, high-skilled human capital, and R&D cooperation also typically increase private R&D. Recent work (Rocchetta et al., 2021) indicates that accounting for non-linearities is one area of research that may refine existing results. Most evaluation studies identify positive policy effects of R&D subsidies on firm performance and R&D inputs, while other results, such as on the innovation-related outputs of R&D, are more mixed (Mar and Massard, 2021). Many empirical studies have shown that research conducted in public laboratories or universities benefits private research (Audretsch et al., 2002; Autant-Bernard, 2001; Cohen et al., 1994 and 2002; Jaffe, 1989; Veugelers & Cassiman, 2005). As such, there is nowadays a widespread understanding that publicly-funded R&D and R&I programmes tend to act as complements to private R&D. Part of the reason for this is that the risk of localised R&D&I spillovers typically leads to the private sector underinvesting in R&D because of their less-than-complete appropriation of the knowledge generated by their own investments. Public funding for private research can, therefore, reduce the gap between the social and private returns of R&D, thereby increasing private investment.

The literature has also paid an increasing amount of attention to the role played by the geography of knowledge spillovers in spurring economic growth and prosperity (Jaffe 1989; Anselin et al. 1997; Audretsch and Feldman, 2004; Autant-Bernard, 2012; Autant-Bernard and LeSage 2011, 2019; Acs, 2022; Buzard et al., 2020; Ganguli et al., 2020; Prenzel et al., 2018; Thompson, 2006). The evidence suggests that there is a direct effect between public support for R&D and additional private-sector R&D investment at the regional level. Yet, while geographical proximity facilitates the flow of knowledge within regions (Buzard et al., 2020; Ganguli et al., 2020; Jaffe et al., 1993), other mechanisms such as non-market interactions (Glaeser and Scheinkman, 2000), technological proximity (Maggioni and Uberti, 2009) and social networks (Crescenzi et al., 2016) also promote the diffusion of knowledge across space between regions. From the literature, we would assume that the complementarities of having good internal knowledge networks (intraregional collaboration) as well as being connected with other places (interregional knowledge collaboration) would be expected to have a positive effect on regional economic prosperity. In particular, the regions that have both strong inter-regional as well as intra-regional knowledge collaboration activities would be expected to benefit the most from knowledge-related activities. However, the specific partner composition of any research collaboration activities would also be expected to shape the precise outcomes. For example, collaborating with higher-developed regions may generate interregional knowledge flows which contribute positively to the economic prosperity of less-developed regions. Indeed, the positive effect of support of collaborative activities in innovation policy (Broekel and Graf, 2006; Cantner and Vannuccini, 2018) has been demonstrated in a context where networks drive the economic and innovative performance of organisations and regions (Breschi and Lenzi, 2016; Broekel, 2015). It is therefore recognised that interregional and even cross-border collaboration strategies could be developed to raise the potential of localised research and innovation activities and economic prosperity in weaker regions (Navarro, 2018). Policies such as cluster or network policies aiming at improving collaboration between co-located actors have been widely used as a catalyst to improve R&D levels and knowledge intensity in various places. The discussion about the importance of accumulating a critical mass of firms and actors that can interact and develop local knowledge spillovers has therefore been the main reasoning behind the support of innovation-oriented cluster or network policies. In different contexts, cluster policy analyses have been found variously to have positive effects on firm innovation (Baptista and Swann, 1998); on positive innovation externalities by other innovative firms in the cluster (Beaudry and Breschi, 2003); on growing industries (Delgado et al., 2014). However, these findings are far from universal, and part of the reason appears to be that the precise nature of the links between knowledge spillovers and knowledge transmission mechanisms shaping the geography of these knowledge spillovers is still not entirely understood (Kekeci et al., 2022).

There is evidence that collaboration-induced knowledge diffusion policy programs have been important in explaining knowledge convergence between European regions (Erdil et al., 2022), while the composition and cohesion of knowledge networks have been seen as some of the drivers of innovation-based economic development at the sub-national level (e.g., Breschi and Lenzi, 2016). For this reason, before our regression analysis, we use social network analysis (SNA) techniques to construct a series of indicators that illustrate the geographical composition of the knowledge networks. We call them interregional and intraregional research collaboration indicators . SNA techniques (Wassermann and Faust, 1994) have recently been used to better understand the overall structure of relationships between policy actors (Giuliani et al., 2016; Töpfer et al., 2019; Graf and Broekel, 2020; N'Ghauran and Autant-Bernard, 2020; Erdil et al., 2022; Basilico et al., 2023). Building on these approaches, our analysis focuses on the effect of the composition of actors on the knowledge networks generated by collaboration in UKRI projects. In particular, we focus on analysing the effect of knowledge generated by actors in different regions (interregional knowledge spillovers), the effect generated by knowledge generated between actors in the same region (intraregional spillovers) and the consequences of having a balanced geographical/spatial knowledge network (inter- x intra- regional spillovers) on regional development and economic cohesion.

3. Hypotheses development: The relationship between R&D collaboration, regional development and levelling up.

During recent decades, publicly-funded R&I schemes have been understood to be crucial for driving economic prosperity and development at a national level. As well as promoting research excellence, publicly-funded R&I funding schemes encourage the establishment of research partnerships in order to increase their value for money by allowing research partners, and thereby the economy in general, to benefit from the resulting knowledge synergies, complementarities and spillovers. However, according to the UK government (HM Government 2022a), a key goal of promoting public support for R&I nowadays is to achieve a more equitable distribution of sub-national gross expenditures on R&I across the UK as a means of fostering regional productivity convergence or 'Levelling Up'. This raises the question as to whether and how publicly-funded R&I schemes can foster regional convergence via the promotion of economic development.

Traditional analyses of the links between R&D and R&I and economic growth have primarily focused on measuring the direct relationships (Aghion et al., 2005), with strong support for a direct effect of R&D and R&I on economic prosperity being widely observed (Aghion and Howitt, 1998; Arrow, 1962; Grossman and Helpman, 1991; Romer, 1990, 1986), while more mixed results have been found regarding the effects on economic convergence (Celli et al., 2021) and cohesion (Crescenzi et al., 2020). Part of the reason for this is that capturing the indirect and induced economic development effects of public R&D and R&I funding is complex (Mar and Massard, 2021). This is because the indirect and induced effects of economic development also depend on the precise nature of the partnership and collaboration mechanisms underpinned by public funding as well as their consequent impacts on the scale and spatial patterns of additional private investments and associated innovation outcomes. Indeed, there is a vast literature on these issues, which is well beyond the scope of this paper, but the key features of this literature are outlined in the online supplementary material.

Importantly, when it comes to the likely impacts of publicly-funded R&D and R&I on regional economic development and interregional convergence or divergence, on the basis of all of the available evidence, we can describe various potential direct and indirect mechanisms for knowledge spillovers and knowledge transmission effects, which may also operate via the mediating effects of private sector investments in business R&D. These various potential mechanisms can be hypothesised thus:

H1a and H1b (path a): There is a direct effect of publicly-funded R&D (projects and grants) on regional business R&D (BERD)

H1a and H1b (path b): There is a direct effect of regional business R&D on regional economic development and economic convergence/divergence

H1a and H1b (path c): There is a potential mediating effect of regional business R&D on the effect of publicly-funded R&D on regional economic development and economic convergence/divergence

H2a: There is a potential mediating effect of regional business R&D on the effect of R&D and intra-regional knowledge collaboration on regional economic development and economic convergence/divergence

H2b: There is a potential mediating effect of regional business R&D on the effect of R&D and inter-regional knowledge collaboration on regional economic development and economic convergence/divergence

H2c: There is a potential mediating effect of regional business R&D on the effect of regionally diversified R&D and knowledge collaboration and economic development and economic convergence/divergence

H3a: There is a potential mediating effect of regional business R&D on the effect of R&D projects with the capital region and regional economic development and economic convergence/divergence

H3b: There is a potential mediating effect of regional business R&D on the effect of R&D funds of projects with the capital region and regional economic prosperity and economic convergence/divergence

We now proceed to examine which of these hypothesised knowledge spillovers and knowledge transmission mechanisms are evident in the UK interregional economic system.

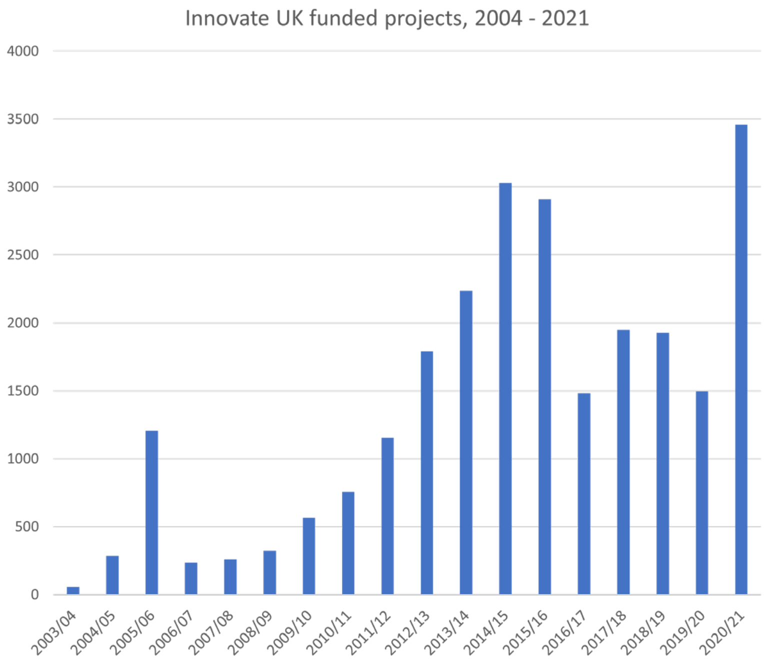
4. Data: UKRI project data and social network construction

In order to examine whether the use of public R&D and R&I funding has contributed to processes of UK regional economic development and regional convergence or divergence, or levelling-up, we analyse the UK Research and Innovation (UKRI) funded projects repository between 2004 and May 2021. This information is complemented with data from ONS and the web-scraping of individual firm information and data from the Companies House website. Our dataset contains 25,122 projects and 44,406 participants. In particular, we use all collaborative research and development (R&D), feasibility, smart and innovation voucher grants, and

Knowledge Transfer Partnerships in 41 UK NUTS2 (ITL2) regions. The UKRI collaborative R&D funding programmes covered nearly half of the funded projects between 2004 and 2021.

By applying the techniques of social network analysis to these uniquely detailed data, we are able to identify diverse types of R&I partnership collaborations according to the type of project, such as whether they are university-industry activities or public-private activities. We are also able to determine their distinct characteristics in terms of the scale and quality of their partnership composition and their partnership leadership. Moreover, we have the detailed post-code information of the participants, such that our dataset allows us the geolocate the distribution of projects and participant involvement. This means that we are able to identify the spatial patterns and any changes in these patterns over time of the spatial distribution of R&I spending and partnership collaboration.

Figure 1. Innovate UK funded projects, 2004-2021.



Source: own elaboration.

As we see in Figure 1, the annual number of UKRI publicly funded projects has increased dramatically over the last two decades, with a post-Brexit lull, followed by an upswing in recent years akin to the pre-Brexit years. We are then able to convert these national data to a regional dataset, as the dataset allows us to allocate the publicly funded project to regions by using the associated geographical postcode information. The funded projects are aggregated to the NUTS2 (ITL2) level based on the participants' geographical information.

Our methodology is to construct a series of research collaboration indicators that can be used as regressors in a series of models that aim to analyse the contribution of UKRI projects to economic development and ultimately levelling up (economic convergence) or divergence. However, before we discuss in detail in the next section the statistical basis of our econometric approach, it is first important to outline the principles of the data linking underpinning the construction of the indicators. We construct regional indicators based on the information of the regional project collaborations, and the results are a series of continuous variables that are built by adding the intra or inter-regional collaboration of all the projects granted for that region.

Table 1. Funded projects construction methodology

	NUMBER OF PARTICIPANTS	PARTICIPANTS' REGION	UKC2	UKD3	UKE2
PROJECT A	2	UKC2, UKD3	1	1	
PROJECT B	2	UKE2, UKE2			1
		SUM	1	1	1

Source: own elaboration.

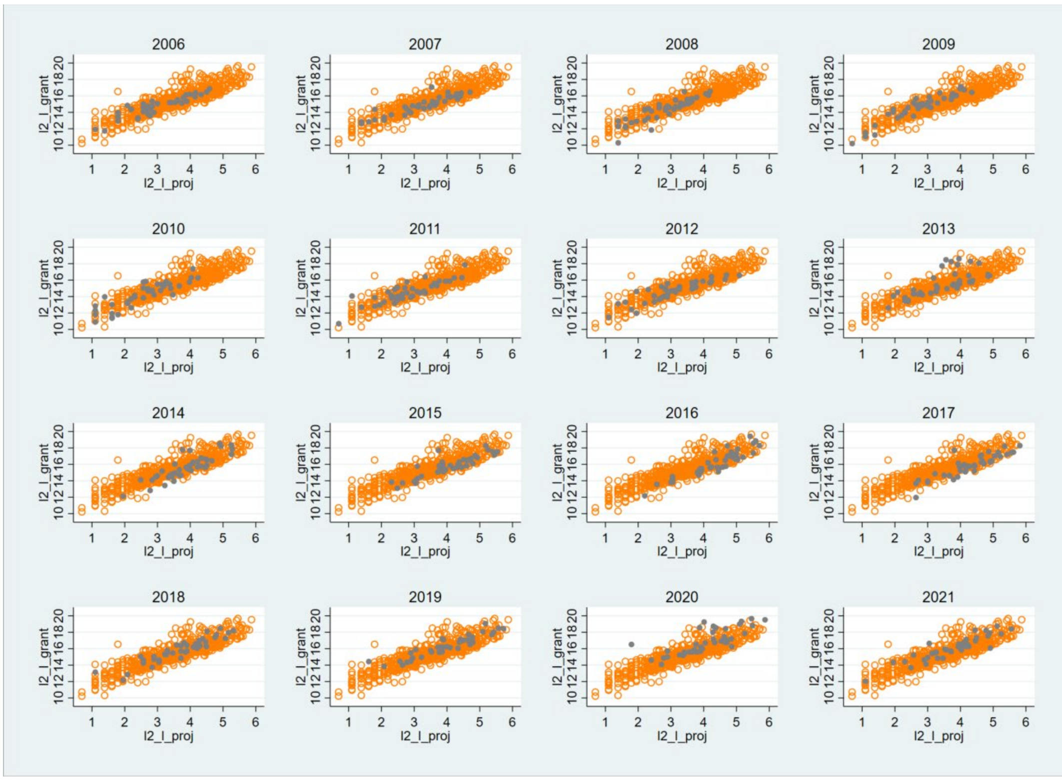
As we see in Table 1, if a project has multiple participants from the same region, the project is counted once for the region. For example, one project has participants from Sunderland (UKC2) and Manchester (UKD3), and another project participants are both from York (UKE2). The UKC2, UKD3, and UKE2 regions are counted to have 1, 1 and 1 project, respectively. Using this allocation method, as shown in Figure 2, at the NUTS1 (ITL1) level, London and the South-East of England are the primary recipients, having received around 46% of UKRI grants between 2004 and 2021. Inner London West and Inner London East appear as the top NUTS2 (ITL2) recipients.

Figure 2. Innovate UK projects, geographical distribution.

Source: own elaboration.

The number of projects and the amount of funds are highly correlated, such that regions that received the highest number of projects also had the highest volume of grants. Figure 3 shows that across the years, the number of publicly funded projects and the volume of grants in the regions are very closely correlated.

Figure 3. Multi-year scatter plot showing the relationship between regional UKRI projects and regional UKRI grants



Source: own elaboration.

The database of UKRI-funded projects now enables us to construct a collaboration network among project participants in the same project. Based on this collaboration network and participants' geographical information, including the postcode, we are able to create a regional collaboration network that is unique for each project. We are then able to aggregate all of these unique collaboration networks in order to depict the overall interregional and intraregional collaboration systems.

For instance, Project C has two participants from Manchester (UKD3) and Derby (UKF1). Project D has one participant from Manchester (UKD3) and two participants from the City of London (UKI3). Collaboration between participants is shown in the last column of Table 2.

Table 2. Knowledge Collaboration Variable Methodology

	NUMBER OF PARTICIPANTS	PARTICIPANTS' REGION	COLLABORATION
PROJECT C	2	UKD3, UKF1	(UKD3, UKF1)
PROJECT D	3	UKD3, UKI3^a, UKI3^b	(UKD3, UKI3^a), (UKD3, UKI3^b) and (UKI3^a, UKI3^b)

Source: own elaboration.

The collaboration column allows us to create a collaboration matrix, as we see in Table 3. The elements in the upper diagonal position of the collaboration matrix signify intraregional collaborations, and the lower diagonal matrix is interregional collaborations.

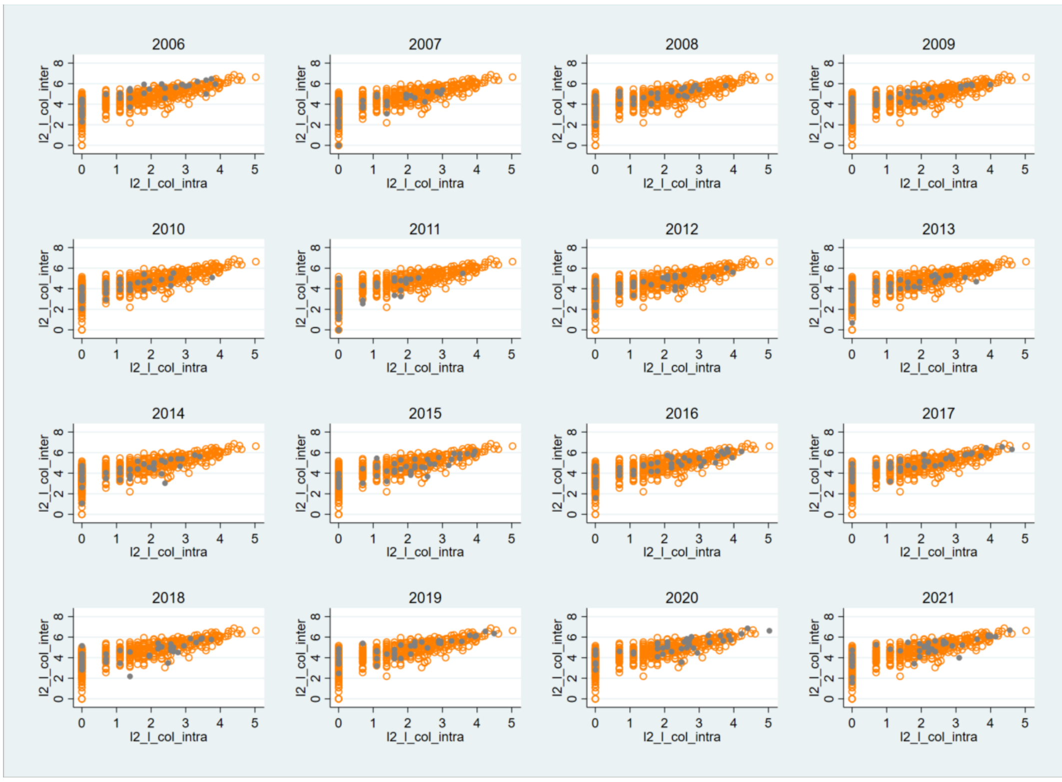
Table 3. Regional Knowledge Collaboration Matrix

REGION 1 / REGION 2	UKD3	UKF1	UKI3
UKD3	0	1	2
UKF1	1	0	0
UKI3	2	0	1
INTRAREGIONAL	0	0	1
INTERREGIONAL	3	1	2

Source: own elaboration.

Importantly, our methodology also allows us to see that intra-regional and interregional collaboration networks are highly correlated. Figure 4 illustrates the relationships between UKRI-funded interregional and intraregional collaboration networks for each year over a 15-year time period. Across all years, regions that have higher *intra*-regional collaboration also tend to have higher levels of *inter*-regional collaboration, and these relationships have remained very stable across all of the study years. The level of balance between regional interregional collaboration and regional intraregional collaboration is measured by the product (combined effect) of *inter*-regional collaboration and *intra*-regional collaboration.

Figure 4. Multi-year scatter plot showing the relationship between regional UKRI intraregional collaboration and regional UKRI interregional collaboration.



Source: own elaboration.

In addition, as Figures A.3 and A.4 in the appendix show, there is a positive association between regions having a diversified regional collaboration portfolio and higher levels of economic development.

In terms of the regional convergence/divergence/Levelling Up discussions, one of the key insights arising from the application of our collaboration construction methodology to the UKRI data is that over the last two decades, in terms of geography, the top cross-regional combination of recipients was between London and the South East. We already know from Figure 2 that London and the South East gained the lion's share of UKRI funding. However, if the lead project-funding recipients in these regions heavily collaborated with other regions, this may reduce the relative dominance of London and the South East. Yet, the initial evidence suggests that this is not the case and that the overall collaborative R&D funding has not contributed to a more geographically balanced distribution of R&I public funds. However, we can explore these issues in more detail.

To do this, we also built a specific index which captures the number of projects that involve project participants from London. Using the same approach that we used to construct the *inter*-regional/*intra*-regional collaboration index, we identified projects that had participants from London and then aggregated the collaboration projects involving London to the NUTS2 (ITL2) level.

In addition to analysing the direct effect of the number of regional projects and the magnitude of regional grants acquired for the NUTS2 (ITL2) region on regional economic prosperity, we also consider the potential mediation effect of public funding on the average regional R&D expenditures in the private sector. Research and innovation policy intends to increase the private R&D generated in the country with the aim of benefiting from the potential multiplicative and complementarity effects of both publicly-funded and privately-funded investments. For this reason, we therefore incorporate the value of regional Business Enterprise Research and Development (BERD) in our regression analysis as a likely mediator of the relationship between publicly-funded R&D and economic prosperity.

BERD captures research and development expenditures in the business enterprise sector. The unit of BERD value is £ million purchasing power standards (PPS) at 2005 prices. The data is from Eurostat (GERD by sector of performance and NUTS2-ITL2 regions). Since the available BERD data only covers up to 2018, this study estimated the BERD values for the period of 2019-2021 by extrapolating the average growth trend of the last 5 years.

Figure A.1. in the online supplementary material appendix shows the regional variability of the association between publicly funded R&D and BERD (in the darker colour). This positive association demonstrates the intended effects of R&D programmes in leveraging private R&D in the region. Regions that have received higher public R&D funding also have higher associated BERD levels.

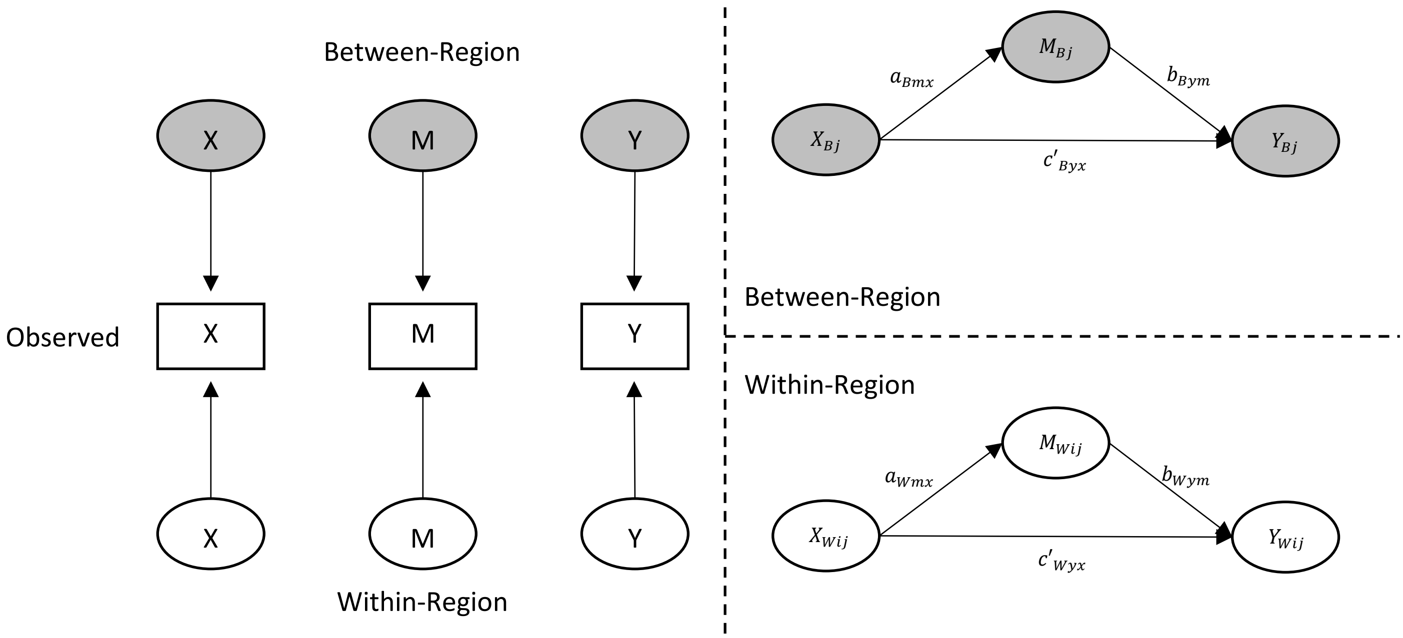
Figure A.2. in the online supplementary material appendix shows the regional between-variability of the association between BERD and regional prosperity (darker dots in the scatter plots). Again, the scatter plots show a mildly positive association.

5. Methodology: Multilevel mediation analysis

The social network regional R&D collaboration indices that we construct are used as independent variables in a model explaining the *inter*-regional (between-region) and *intra*-regional (within-region) outcomes of UKRI interventions, including mediation effects, alongside other potential explanatory and control variables. In order to examine whether regional R&D mediates the effect of publicly-funded R&D and collaboration on economic development and regional growth, and also to account for the hierarchical structure of our data, we followed the general multilevel mediation approach developed by Preacher et al. (2011). Multilevel Structural Equation modelling allows for incorporating mediation in order to capture both the direct and indirect (via business enterprise R&D) potential effects of UKRI support and collaboration on regional prosperity (measured as GDP and GDP per head 2-years and 4-years later) and the relative growth across regions (convergence/divergence/levelling-up).

Our multilevel mediation panel data model is depicted in Figure 5. The left panel shows the multilevel structure of our model. The *within*-regional level is depicted using white ellipses, while the *between*-regional level of our data is shown with grey ellipses. The decomposition of observed variables (X independent variables; M mediator and Y output variable) is split into their latent within-regional variation and the between-regional variation. Our model estimates two mediation regression models at the within-region and between-region levels.

Figure 5. Multilevel mediation model. The left panel shows the decomposition of observed variables into their latent within-region (white ellipses) and between-region (grey ellipses). The right panels show the model estimated at the within- and between-region levels.



As depicted in Figure 5, our data have a clustered structure with regional observations nested within regions, so multilevel techniques are employed in order to obtain unbiased standard errors. Ordinary regression analyses do not take into account the clustered data structure, and therefore, they underestimate standard errors, with results in overestimating the significance of the relationships. Although a hierarchical linear model (HLM) is commonly used for a nested data structure (Çetin and Aşkun, 2018; Vauclair et al., 2015), several papers published over the last decade have shown that HLM is more restricted in mediation analysis for two reasons (Preacher et al., 2011, 2010). First, HLM cannot accommodate mediation pathways with upper-level mediators or outcome variables, and second, MLM conflates the effects of Between-Level and Within-level (Level 1) components on other Level 1 components (MacKinnon, 2008; Zhang et al., 2009).

Although our main focus is on the between-cluster relationships – i.e., the *inter*-regional differences - it is important to differentiate the relationships at the two levels rather than combining them into a single estimate within the indirect effect (Zhang et al., 2009). One option that has recently been developed is a mediation analysis within the multilevel structural equation modelling (MSEM) framework. MSEM approach outperforms HLM as the *between* and *within* parts of all variables are separated, and the direct and indirect effects are examined at each level. MSEM provides unbiased estimates of the between-group indirect effect by treating the cluster-level component of the Level 1 are latent.

A sample two-level model is presented here:

Within-region model.

We analysed how within-region direct and indirect effects of UKRI support-related measurements impact regional performance. More precisely, we used regional performance indicators at time *t* and regressed them onto regional business R&D at time *t−1* and UKRI support-related measurements at time *t−2*. This method was used to observe the within-region delayed impact of regional business R&D on regional performance (path b_{Wym}) and the within-region delayed effect of UKRI support-related measurements on regional performance (path c'_{Wyx}). Additionally, regional business R&D was regressed on UKRI support-related measurements to evaluate the within-region delayed influence of exposure to UKRI support-related measurements on regional business R&D (path a_{Wmx}). Following Preacher et al. (2010), we computed within-region indirect effects as the product of the average within-region a and b paths. The within-region total effects were then determined by adding the direct effect (path c'_{Wyx}) to the indirect effect (path a_{Wmx} * path b_{Wym}).

$$M_{Wij} = v_{Wm} + a_{Wmx}X_{Wij} + \varepsilon_{Wm,ij} \qquad (1)$$

$$Y_{Wij} = v_{Wy} + b_{Wym}M_{Wij} + c'_{Wyx}X_{Wij} + \varepsilon_{Wy,ij} \qquad (2)$$

Combined:

$$Y_{wij} = v_{wy} + b_{Wym}\left(v_{Wm} + a_{Wmx}X_{Wij} + \varepsilon_{Wm,ij}\right) + c'_{Wyx}X_{Wij} + \varepsilon_{Wy,ij} \qquad (3)$$

$$Y_{wij} = (v_{wy} + b_{Wym}v_{Wm}) + (a_{Wmx}b_{Wym} + c'_{Wyx})X_{Wij} + b_{Wym}\varepsilon_{Wm,ij} + \varepsilon_{Wy,ij} \qquad (4)$$

Between-region model.

We assessed a comparable model considering the latent between-region components of each variable (refer to the top-right panel of Figure 5). At this between-region level, Path a_{Bmx}

illustrates the impact of UKRI support-related measurements on the average levels of regional business R&D. Path b_{Bym} delineates the relationship between average levels of business R&D and average levels of regional performance. Meanwhile, path c'_{Byx} conveys the direct connection between the average allocation of UKRI support-related measurements and the average levels of regional performance. Just like in standard single-level mediation, the between-region indirect effect was determined by multiplying the a and b paths, and the between-region total effect was computed by adding the direct (path c'_{Byx}) and indirect effects (path a_{Bmx} * path b_{Bym}).

$$M_{Bj} = v_{Bm} + a_{Bmx}X_{Bj} + \varepsilon_{Bm,j} \qquad (5)$$

$$Y_{Bj} = v_{By} + b_{Bym}M_{Bj} + c'_{Byx}X_{Bj} + \varepsilon_{By,j} \qquad (6)$$

Combined:

$$Y_{Bj} = v_{By} + b_{Bym}(v_{Bm} + a_{Bmx}X_{B,j} + \varepsilon_{Bm,j}) + c'_{Byx}X_{Bj} + \varepsilon_{By,j} \qquad (7)$$

$$Y_{Bj} = (v_{By} + b_{Bym}v_{Bm}) + (a_{Bmx}b_{Bym} + c'_{Byx})X_{Bj} + b_{Bym}\varepsilon_{Bm,j} + \varepsilon_{By,j} \qquad (8)$$

where m_{Wij} is the within-region level mediator for observation i nested within the region j, a_{Wmx} is the fixed slope of x on m for each region and $\varepsilon_{Wm,ij}$ is the within-region level error term with the variance of σ^2_{Wm}. y_{Wij} is the within-region level outcome for the observation i nested within the region j, b_{Wym} is the fixed slope of y on m for each region, c'_{Wyx} is the fixed slope of y on x for each region and $\varepsilon_{Wy,ij}$ is the within-region level error term with the variance of σ^2_{Wy}. At the between-region level, all terms are as before and have similar interpretations, except for the B parts, which apply to regions, and the W parts, which apply to observations which are nested within regions. The indirect effects at the within- and between-region level are $a_{Wmx}b_{Wym}$ and $a_{Bmx}b_{Bym}$ respectively.

The dataset consists of information at the NUTS2 (ITL2) region level from the UK, covering the period from 2004 to May 2021. For every NUTS2 (ITL2) region, we have data on projects and funds across these 18 years, providing multiple observations for the same region. Within-region variability refers to the fluctuations or deviations that occur within a single region, focusing on variations from its average or typical activity or performance. In contrast, between-region variability highlights the differences or variations existing among different regions, comparing the attributes or characteristics of one region to another.

Considering our set of independent and dependent variables, we ran separate models for each UKRI support-related measurement and each type of regional performance indicator. We fit the model using *R*-lavaan package. In addition, as well as examining the construction and composition of research partnerships within and between regions, we also control for characteristics of the regional economy which may influence regional performance and convergence processes.

Control variables: regional environment

In terms of additional control variables alongside the collaboration indices and mediation effects, given the importance of the economic structure in explaining economic development and convergence (Percoco, 2017; Pina and Sicari, 2021), we use the Krugman industrial specialisation regional index to capture these features. This index provides a relative measure of specialisation by comparing the industry structure of an area with the average industry structure of a reference group of areas, which in this case is the country. The Krugman index is here constructed to reflect sectoral specialisation among the NUTS2 (ITL2) subregions in the UK.

We also include regional population density as a way of capturing various agglomeration-related effects (Andersson et al., 2007; Behrens et al., 2014; Combes et al., 2012). Agglomeration potentially impacts processes of firm competition and competition (Delgado et al., 2010) as well as new firm formation and start-ups (Enright, 2000; Manning, 2008), as well as affecting the impacts of policy interventions (Bachtrögler et al., 2020), and all of these potential processes could influence the outcomes of UKRI interventions. Following the literature, we therefore include the number of individuals per square kilometre by NUTS2 (ITL2) subregion in our analysis.

Dependent variables: Economic Development and Economic Convergence (Levelling up).

We use two main dependent variables for the regional economic development and convergence models. First, in order to capture the direct and indirect effects of regional funds on economic development, we use a measure of regional productivity, GDP per head at 2019 prices, included in the models as 2-year and 4-year later than when the UKRI funds were first acquired. This is in order to control for any potential time delays in translating R&D support instruments into economic prosperity.

With the aim to capture the potential effects of publicly funded R&D and private R&D on economic convergence or levelling up, we construct the following Levelling up Index:

$$Economic\ convergence = \frac{Regional\ GDP_t}{UK\ GDP_t} - \frac{Regional\ GDP_{t-1}}{UK\ GDP_{t-1}} \quad (9)$$

This measure indicates the change in the relative position of the region in terms of development or productivity compared to the whole of the UK. For relatively poorer regions, a positive value of the levelling-up index means that the poor region performed better than in the previous year, which indicates a process of convergence. However, when a relatively rich region records a positive value of the index, this provides evidence of interregional divergence because the rich region is moving further ahead from the average. A region is considered relatively rich if its GDP per head is higher than the UK GDP per head over the same period. Therefore, to have a consistent interpretation of the positive value for the index, we multiply the levelling-up index by minus one for relatively rich regions, already positioned at or above the average. Thus, a positive value of our levelling-up index now unambiguously refers to interregional economic convergence, while a negative one indicates interregional economic divergence.

$$Economic\ convergence\ index_{r,t} = \begin{cases} Rich\ regions: -\left[\left(\frac{GDP_{r,t}}{GDP_t}\right) - \left(\frac{GDP_{r,t-1}}{GDP_{t-1}}\right)\right] \\ Poor\ regions: \left(\frac{GDP_{r,t}}{GDP_t}\right) - \left(\frac{GDP_{r,t-1}}{GDP_{t-1}}\right) \end{cases} \quad (10)$$

Table 4 summarises the main variables in our analysis, including the definition, data sources and time coverage, and Table 5 reports descriptive statistics for these variables.

Table 4. Variables description

	Name of the variable	Definition	Data source	Time period
1	Regional Projects	Total regional projects	UKRI	2004 – 2021
2	Regional Funds	Total regional funds	UKRI	2004 – 2021
3	Intraregional Collaboration	Regional number of intraregional collaborations	Index constructed from social network analysis	2004 – 2021
4	Interregional Collaboration	Regional number of interregional collaborations	Index constructed from social network analysis	2004 – 2021
5	Diversified Knowledge Collaboration	Regional intraregional collaboration and interregional collaboration	Index constructed from social network analysis	2004 – 2021
6	Collaboration with the Capital region Projects	Regional number of projects that include London	Index constructed from social network analysis	2004 – 2021
7	Collaboration with the Capital region Funds	Regional funds associated with projects that include London	Index constructed from social network analysis	2004 – 2021
8	Krugman Specialisation Index	Sectoral specialisation among the NUTS2 (ITL2) subregions	ONS	1998 – 2016
9	Regional Population Density	Persons per square kilometre	Eurostat	2004 – 2018
10	Regional Business R&D	Regional BERD	Eurostat	2004 – 2018
11	Regional Development – Productivity	Regional GDP per head	ONS	2004 – 2021
12	Economic convergence (Levelling Up)	Regional economic Convergence towards the UK Regional Average	Index constructed from social network analysis	2004 - 2021

Table 5. Descriptive statistics

	Variable	Obs	Mean	Std. dev.	Min	Max
1	Regional Projects	653	3.487199	1.044818	0.693147	5.869297
2	Regional Funds	653	15.394	1.589	10.217	19.669
3	Intraregional Collaboration	653	4.377	1.102	0.000	6.870
4	Interregional Collaboration	653	1.407	1.279	0.000	5.024
5	Diversified Knowledge Collaboration	653	5.125	3.151	0.000	11.657
6	Collaboration with the Capital region Projects	653	2.107	1.134	0.000	5.472
7	Collaboration with the Capital region Funds	653	13.475	3.391	0.000	19.189
8	Krugman Specialisation Index	653	0.254	0.105	0.073	0.676
9	Regional Population Density	653	6.035	1.410	2.407	9.366
10	Regional Business R&D	611	5.506	1.179	2.676	7.797
11	Regional Development – Productivity	735	10.262	0.335	9.840	12.250
12	Economic convergence (Levelling Up)	694	0.424	3.823	-13.695	78.201

Note. All variables have been transformed into logarithmic values except for the Krugman Specialisation Index and Economic Convergence (Levelling Up).

Table 6. Correlation Matrix

		1	2	3	4	5	6	7	8	9	10	11	12
1	Regional Projects	1.000											
2	Regional Funds	0.8790*	1.000										
3	Intraregional Collaboration	0.7314*	0.7211*	1.000									
4	Interregional Collaboration	0.8155*	0.7809*	0.7646*	1.000								
5	Diversified Knowledge Collaboration	0.7800*	0.7718*	0.8368*	0.9037*	1.000							
6	Collaboration with the Capital region Projects	0.7972*	0.7460*	0.8711*	0.6820*	0.7321*	1.000						
7	Collaboration with the Capital region Funds	0.6162*	0.6527*	0.6940*	0.4921*	0.5503*	0.7308*	1.000					
8	Krugman Specialisation Index	-0.0935*	-0.1063*	-0.1320*	-0.1028*	-0.1036*	0.032	-0.0947*	1.000				
9	Regional Population Density	0.4160*	0.3651*	0.4222*	0.2620*	0.3027*	0.5914*	0.4177*	0.1600*	1.000			
10	Regional Business R&D	0.6186*	0.5841*	0.6481*	0.5402*	0.5606*	0.6011*	0.4338*	-0.2722*	0.2101*	1.000		
11	Regional Development – Productivity	0.4042*	0.3465*	0.3834*	0.3574*	0.3394*	0.5283*	0.2749*	0.5878*	0.4244*	0.3598*	1.000	
12	Levelling Up	0.0936*	0.0959*	0.0909*	0.1208*	0.0934*	0.1453*	0.068	0.2664*	0.1818*	0.011	0.3968*	1.000

Note: * denotes prob <.05

Table 7. Interclass Correlation Coefficient (ICC) main variables

	ICC
H1a: Regional projects	0.55
H1b: Regional funds	0.58
H2a: Intraregional collaboration	0.611
H2b: Interregional collaboration	0.665
H2c: Diversified Knowledge collaboration	0.618
H3a: Collaboration with the Capital region projects	0.749
H3b: Collaboration with the Capital region grants	0.375

Table 8. Interclass Correlation Coefficient (ICC) per dependent variable and controls

	BERD	**GDP per head**	**Levelling up**	**Population density**	**Krugman Specialisation Index**
ICC	0.924	0.983	0.15	0.999	0.96

As we see in Table 6, Pearson correlation coefficients show that all variables in the mediation model correlate significantly with each other at the regional level. Regional business R&D correlates with UKRI projects at r = 0.62, p<.05 and with UKRI grants at r = 0.58, p<.05. Regional business R&D correlates with regional productivity at r = 0.36, p<.05 but does not have a significant association with the levelling-up index. Finally, we can see an association between publicly-funded R&D and regional productivity of around 0.40 for projects and 0.35 for grants and a weak 0.09 and 0.10 positive association, respectively, between publicly-funded projects and publicly-funded grants and levelling up.

As we see in Table 7, the interclass correlation coefficients (ICC) from the multilevel analyses indicate that more than half of the total variance in regional publicly funded UKRI R&D (55% for projects and 58% for grants) are associated with the *inter*-regional differences between regions, rather than intra-regional differences. The coefficients are even higher for all the R&D collaboration variables, with the highest being collaborating with the capital region (75%). Similarly, Table 8 underscores that the majority of the variance in both endogenous and control variables also primarily stem from *inter*-regional differences, rather than intra-regional differences. In other words, the ICC statistics from Tables 7 and 8, along with the scatter matrix in the appendix, indicate that there is a stronger between-region component than within-region component in our models for economic prosperity and economic convergence. That is to say that the bulk of the variance in these models is attributed to differences between regions, rather than within them. As a result, we observe that most of the significant coefficients are at the between-region level, and in all of our models, the number of regional projects has a larger economic development effect than the scale of the funds deployed.

6. Results: The Intended and Unintended Regional Effects of Research and Innovation Policy

Table 9[1] presents the path analysis results of our regional economic productivity/prosperity model in which GDP per head (t+2 year) is the dependent variable for the hypothesized relationships. Table 10[2] presents the model with economic convergence in t+2 as the dependent variable. The top part of the table presents the coefficients for the within part of the model (within-group comparison, individual regional performance) – how these coefficients affect UK regions independently, while the bottom part of the table refers to the between part of the model (between regions comparison) – how these relationships differ between regions.

As an example of the interpretation of our results, we found a significant and positive effect on the direct relationship between the number of regional projects on regional private sector R&D (a path, between (region) level 1.323***), a direct effect between BERD and GDP per capita (both individually 0.010+ and between regions 0.094*) and a positive indirect effect between the number of projects and regional GDP per capita per each region (within -regional – level, last column) and between regions (0.124*). These results support our hypothesis 1A that the number of publicly funded projects had a positive effect on regional prosperity; the model seems to point out that the major effects are happening when comparing regions (between component) as seen in the magnitude and significance of the coefficients.

[1] See full regression results associated with Table 9 in Table A1 in the appendix
[2] See full regression results associated with Table 10 in Table A2 in the appendix

In Table 9, our results find strong support for the argument that regional projects and regional grants have both a direct (path a) and indirect effect (path b) on the levels of regional economic prosperity, measured as GDP per head (Table 9), as well as the mediating defects of the BERD. In particular, it is the between-region collaborations in which these knowledge-investment transmission mechanisms operate rather than intra-regional collaborations. Moreover, collaborations with London play an even stronger role, and especially if the projects are diversified. In other words, we find strong support for all of our Hypothesis 1a-3b with regard to the links between regional productivity and publicly-funded R&D.

Table 9 Mediation of the effect of BERD on UKRI projects/grants and regional economy prosperity (measured as GDP per head in t+2)

		a path		b path		Indirect effect [95% CI]	
	Within (region) level						
H1a	Regional projects path via BERD	0.020	(0.024)	0.010+	(0.005)	0.000**	[0.000, 0.001]
H1b	Regional grants path via BERD	-0.005	(0.016)	0.012*	(0.005)	0.000	[0.000, 0.000]
H2a	Intraregional collaboration path via BERD	0.033+	(0.017)	0.010+	(0.005)	0.000**	[0.000, 0.001]
H2b	Interregional collaboration path via BERD	0.046*	(0.021)	0.009	(0.005)	0.000**	[0.000, 0.001]
H2c	Inter*Intra collaboration path via BERD	0.006	(0.007)	0.011*	(0.006)	0.000	[0.000, 0.000]
H3a	London collaboration projects path via BERD	0.033	(0.025)	0.010+	(0.005)	0.000**	[0.000, 0.001]
H3b	London collaboration grants path via BERD	-0.006	(0.005)	0.013*	(0.006)	0.000	[0.000, 0.000]
	Between (region) level						
H1a	Regional projects path via BERD	1.323***	(0.174)	0.094*	(0.044)	0.124**	[0.007, 0.242]
H1b	Regional grants path via BERD	0.770***	(0.126)	0.121**	(0.038)	0.093**	[0.029, 0.157]
H2a	Intraregional collaboration path via BERD	0.728***	(0.149)	0.115***	(0.032)	0.084**	[0.028, 0.139]
H2b	Interregional collaboration path via BERD	1.113***	(0.147)	0.121**	(0.043)	0.135**	[0.035, 0.235]
H2c	Inter*Intra collaboration path via BERD	0.314***	(0.058)	0.129***	(0.035)	0.041**	[0.015, 0.066]
H3a	London collaboration projects path via BERD	1.139***	(0.157)	0.091*	(0.039)	0.104**	[0.012, 0.196]
H3b	London collaboration grants path via BERD	0.599***	(0.095)	0.131*	(0.053)	0.078**	[0.013, 0.143]

Note. Standard errors are shown in parentheses. CI = confidence interval.
+ p < .1, * p < .05, ** p < .01, *** p < .001

In terms of economic convergence, the results reported in Table 10 demonstrate that inter-regional collaborations also foster regional economic convergence and again, that collaborations with London and also diversified project portfolios also play additional convergence-related roles. As such, Hypotheses 2a-3b are again supported, but only in terms of path a, whereas beyond this direct effect, there is no indirect effect nor any mediated or induced effect on convergence.

Table 10. Mediation of the effect of BERD on UKRI projects/grants and regional economy convergence in t+2

		a path		b path		Indirect effect [95% CI]	
	Within (region) level						
H1a	Regional projects path via BERD	0.020	(0.024)	-0.492	(0.327)	-0.010	[-0.036, 0.016]
H1b	Regional grants path via BERD	-0.005	(0.016)	-0.476	(0.327)	0.002	[-0.013, 0.017]
H2a	Intraregional collaboration path via BERD	0.033+	(0.017)	-0.463	(0.328)	-0.015	[-0.041, 0.011]
H2b	Interregional collaboration path via BERD	0.046*	(0.021)	-0.425	(0.328)	-0.019	[-0.053, 0.015]
H2c	Inter*Intra collaboration path via BERD	0.006	(0.007)	-0.478	(0.327)	-0.003	[-0.011, 0.005]
H3a	London collaboration projects path via BERD	0.033	(0.025)	-0.463	(0.327)	-0.015	[-0.046, 0.016]
H3b	London collaboration grants path via BERD	-0.006	(0.005)	-0.488	(0.328)	0.003	[-0.003, 0.009]
	Between (region) level						
H1a	Regional projects path via BERD	1.323***	(0.174)	-0.037	(0.218)	-0.048	[-0.616, 0.519]
H1b	Regional grants path via BERD	0.770***	(0.126)	0.057	(0.184)	0.044	[-0.234, 0.322]
H2a	Intraregional collaboration path via BERD	0.728***	(0.149)	-0.061	(0.150)	-0.045	[-0.260, 0.171]
H2b	Interregional collaboration path via BERD	1.113***	(0.147)	-0.034	(0.207)	-0.037	[-0.489, 0.414]
H2c	Inter*Intra collaboration path via BERD	0.314***	(0.058)	0.033	(0.166)	0.010	[-0.092, 0.113]
H3a	London collaboration projects path via BERD	1.139***	(0.157)	0.057	(0.200)	0.065	[-0.382, 0.512]
H3b	London collaboration grants path via BERD	0.599***	(0.095)	0.015	(0.257)	0.009	[-0.292, 0.310]

Note. Standard errors are shown in parentheses. CI = confidence interval.
+ p < .1, * p < .05, ** p < .01, *** p < .001

In the online supplementary material appendix, Tables A3 and A4 repeat the models reported in Tables 9 and 10, but with 4-year lags. Our results are very similar when comparing the results in 2-year and 4-year lag structures, thereby confirming their stability.

Table 11. Model fit indices of mediation of the effect of BERD on UKRI projects/grants and regional economy prosperity in t+2

	CFI	**NFI**	**NNFI**	**RFI**	**RMSEA**	**SRMR**
H1a: Regional projects	0.666	**1.000**	**1.000**	**1.000**	**0.000**	**0.029**
H1b: Regional funds	0.693	**1.000**	**1.000**	**1.000**	**0.000**	**0.028**
H2a: Intraregional collaboration	0.622	**1.000**	**1.000**	**1.000**	**0.000**	**0.024**
H2b: Interregional collaboration	0.618	**1.000**	**1.000**	**1.000**	**0.000**	**0.022**
H2c: Diversified Knowledge collaboration	0.894	**1.000**	**1.000**	**1.000**	**0.000**	**0.025**
H3a: Collaboration with the Capital region projects	0.606	**1.000**	**1.000**	**1.000**	**0.000**	**0.023**
H3b: Collaboration with the Capital region grants	0.923	**1.000**	**1.000**	**1.000**	**0.000**	**0.023**

For each index, an acceptable level of fit is indicated as follows: CFI >0.95; NFI > 0.95; NNFI > 0.95; RMSEA < 0.05; RFI > 0.90; SRMR < 0.08.

Table 12 Model fit indices of Mediation of the effect of BERD on UKRI projects/grants and regional economy convergence in t+2

	CFI	**NFI**	**NNFI**	**RFI**	**RMSEA**	**SRMR**
H1a: Regional projects	0.911	**1.000**	**1.000**	**1.000**	**0.000**	**0.029**
H1b: Regional funds	0.888	**1.000**	**1.000**	**1.000**	**0.000**	**0.028**
H2a: Intraregional collaboration	0.901	**1.000**	**1.000**	**1.000**	**0.000**	**0.025**
H2b: Interregional collaboration	0.901	**1.000**	**1.000**	**1.000**	**0.000**	**0.023**
H2c: Diversified Knowledge collaboration	0.901	**1.000**	**1.000**	**1.000**	**0.000**	**0.025**
H3a: Collaboration with the Capital region projects	0.903	**1.000**	**1.000**	**1.000**	**0.000**	**0.024**
H3b: Collaboration with the Capital region grants	0.916	**1.000**	**1.000**	**1.000**	**0.000**	**0.024**

For each index, an acceptable level of fit is indicated as follows: CFI >0.95; NFI > 0.95; NNFI > 0.95; RMSEA < 0.05; RFI > 0.90; SRMR < 0.08.

As well as robustness and stability with respect to time lags, our models and results also display strong goodness-of-fit features, and here we provide tables with the model fit indices for all our models. We selected multiple fit criteria to assess model fit from different aspects of the model. Specifically, six fit indices were selected, and the acceptable level of fit is listed as follows: the normed fit index (NFI) > 0.95; the non-normed fit index (NNFI) > 0.95; comparative fit index (CFI) > 0.95; the root mean square error of approximation (RMSEA) < 0.06; the standardized root mean square residual (SRMR) < 0.08; the relative fit index (RFI) close to 1 (Bearden and Netemeyer, 1999; Gefen et al., 2000; Hu and Bentler, 1999). The model fit indices are reported in Table 11 and Table 12. The results show that almost all the models fit the thresholds (bold values in our model fit indices tables indicate that the model fits the index threshold).

Overall, our results show that the effect of publicly-funded research on regional productivity is mediated by the effect of regional private R&D measured as (BERD) Business Enterprise Research and Development. Second, the evidence shows that private R&D can only account for the effect of publicly-funded R&D and collaboration on regional productivity but not on regional economic convergence or levelling up. Third, the knowledge-investment transmission mechanisms primarily influence regional economic productivity and prosperity via between-region collaborations, rather than intra-regional collaborations. Fourth, inter-regional collaborations also foster regional economic convergence, although this is primarily associated with collaborations with London, as well as having diversified project portfolios.

In terms of the Levelling Up agenda and its associated missions, our results provide some robust support for such an approach as well as highlighting some challenges. While we have found evidence of a positive effect of all forms of knowledge collaboration on private R&D as well as direct and indirect effects on regional productivity, our results also show that the convergence-related effects of interregional knowledge collaboration are enhanced by also having projects collaborating with London. This implies that knowledge connectivity and institutional connectivity with London is central to achieving regional convergence and Levelling Up. As we have already reported, knowledge-related connections with London are already dominated by the South and East of England, so to the extent that Knowledge collaborations with London promote regional economic convergence, this Levelling Up effect appears to be primarily contained within the more prosperous regions of the South and South East of England.

While UKRI investments are seen to enhance regional prosperity both directly and indirectly, historically, the regional convergence effects of UKRI investments have not spurred Levelling Up on a nationwide scale, as the Levelling Up White Paper has advocated for. However, the UKRI investments were never explicitly designed with nationwide Levelling Up as a primary part of their remit. If the Levelling Up agenda and its mission are indeed to be more generally adopted in the wider UK government and policy agenda, the insights from this research may help to guide a re-think or redesign of the policy schema. Encouraging links with London researchers from more peripheral non-southern regions may be a key priority, as well as fostering productivity and convergence without links to London, would both appear to be priority areas for the reform of publicly-funded knowledge-collaboration policies.

7. Conclusions

In 2022, the Government published its Levelling Up the United Kingdom White Paper to address and narrow the economic and social disparities across the UK regions. The white paper argues that a "fundamental rewiring" of the system of decision-making, locally and nationally, is required to address geographical disparities. To do that, apart from others, the government is introducing the R&D mission that aims at increasing the R&D public support in the areas outside the Greater South East. The document argues that this change has to come in partnership with the private sector, arguing that collaboration is essential in order to ensure economic prosperity across the country.

In this paper, we have examined the context in which such a Levelling Up R&D mission would operate. We have done this by analysing the relationship between publicly funded R&D and knowledge collaboration on regional economic prosperity, convergence and levelling up in the UK NUTS2 (ITL2) regions for the period 2004-2021. Our approach has considered a wide range of mediating pathways between research funding and regional development using a novel multilevel methodology. The results from our multilevel mediation panel data model provide new evidence and insights into the effects of different types of knowledge collaborations supported by publicly-funded sources.

Our results suggest that to increase regional economic development and convergence in the UK, further project selection procedures should be implemented in some research-related funding streams, ensuring that the projects promote the creation of knowledge flows between and within regions. In particular, it is also recommended to support further engagement in interregional collaboration and joint innovation projects involving regions of different levels of development, and especially outside of the wider south and south east of England. However, finding ways to do this without compromising the quality of the programmes and projects is essential (Crescenzi et al., 2020). This often requires the broader consideration of a wider set of issues. For example, regional connectedness can be affected by policies implemented at different levels of governance and in other regions; indeed, regional territories can be both deliberate targets of national policies but also places where the unintended impacts of policies made at other levels of governance are felt (McCann and Ortega-Argilés, 2015; Uyarra and Flanagan, 2010). This includes spillover effects of certain policies, such as the building of large scientific infrastructure beyond regions' administrative borders(OECD, 2013) or supporting digital infrastructures in macro-regional areas. Careful consideration of such potential knowledge spillover mechanisms, including the portfolio of local knowledge assets, the regional institutional set-up, and the commercial and governance linkages with other regions, may also be important aspects of any research funding programme in which Levelling Up missions are an important element. Indeed, UKRI has already piloted exactly this type of research-funding programme, namely the £316million 'Strength in Places Fund'[3], and this prototype research and innovation funding programme could form the template for a greatly expanded Levelling Up mission aimed at fostering a nationwide regional convergence agenda.

A final word of caution relates to the fact that the UKRI Innovate UK project database only partly considers a share of the totality of publicly-funded research in the UK, with other publicly funded projects from alternative public sources (Research Councils, European

[3] https://www.ukri.org/what-we-do/browse-our-areas-of-investment-and-support/strength-in-places-fund/

Commission Funded projects, etc.) not being considered in this analysis. Whether the funding patterns and impacts displayed by other funding sources differ markedly from the UKRI portfolio remains to be analysed.

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Appendix

Table A1. Mediation of the effect of BERD on UKRI projects/grants and regional economy prosperity (measured as GDP per head 2-year later) – Full model linked to Table 9

		H1a Regional projects		H1b Regional grants		H2a Intraregional coll.		H2b Interregional coll.		H2c Diversified Know. Coll.		H3a Coll with London projects		H3b Coll. with London grants	
		Estimate	**95% CI**	**Estimate**	**95% CI**	**Estimate**	**95% CI**	**Estimate**	**95% CI**	**Estimate**	**95% CI**	**Estimate**	**95% CI**	**Estimate**	**95% CI**
Within-region															
BERD ~ X	(path a)	0.020	[-0.026, 0.067]	-0.005	[-0.035, 0.026]	0.033+	[-0.001, 0.066]	0.046*	[0.005, 0.086]	0.006	[-0.007, 0.020]	0.033	[-0.016, 0.081]	-0.006	[-0.015, 0.004]
GDP ~ BERD	(path b)	0.010+	[0.000, 0.020]	0.012*	[0.002, 0.023]	0.010+	[-0.001, 0.021]	0.009	[-0.002, 0.019]	0.011*	[0.000, 0.022]	0.010+	[0.000, 0.021]	0.013*	[0.002, 0.024]
GDP ~ X	(path c)	0.027	[0.022, 0.032]	0.012	[0.009, 0.016]	0.010	[0.006, 0.014]	0.017	[0.012, 0.022]	0.003	[0.002, 0.005]	0.015	[0.009, 0.022]	0.002	[0.000, 0.003]
Indirect effect	(a*b)	0.000**	[0.000, 0.001]	0.000	[0.000, 0.000]	0.000**	[0.000, 0.001]	0.000**	[0.000, 0.001]	0.000	[0.000, 0.000]	0.000**	[0.000, 0.001]	0.000	[0.000, 0.000]
Total effect	(c + ab)	0.027**	[0.022, 0.033]	0.012**	[0.009, 0.016]	0.011**	[0.006, 0.015]	0.017**	[0.012, 0.022]	0.003**	[0.002, 0.005]	0.016**	[0.010, 0.022]	0.001**	[0.000, 0.003]
Between-region															
BERD ~ X	(path a)	1.323***	[0.981, 1.665]	0.770***	[0.523, 1.017]	0.728***	[0.435, 1.021]	1.113***	[0.824, 1.401]	0.314***	[0.199, 0.428]	1.139***	[0.831, 1.447]	0.599***	[0.414, 0.785]
GDP ~ BERD	(path b)	0.094*	[0.007, 0.181]	0.121**	[0.047, 0.195]	0.115***	[0.052, 0.177]	0.121**	[0.037, 0.206]	0.129***	[0.061, 0.198]	0.091*	[0.014, 0.168]	0.131*	[0.027, 0.234]
GDP ~ X	(path c)	0.142	[-0.008, 0.291]	0.062	[-0.021, 0.144]	0.088	[0.013, 0.163]	0.073	[-0.049, 0.196]	0.023	[-0.010, 0.056]	0.137	[0.020, 0.253]	0.029	[-0.055, 0.114]
Indirect effect	(a*b)	0.124**	[0.007, 0.242]	0.093**	[0.029, 0.157]	0.084**	[0.028, 0.139]	0.135**	[0.035, 0.235]	0.041**	[0.015, 0.066]	0.104**	[0.012, 0.196]	0.078**	[0.013, 0.143]
Total effect	(c + ab)	0.266**	[0.174, 0.358]	0.155**	[0.091, 0.218]	0.172**	[0.105, 0.239]	0.208**	[0.127, 0.290]	0.064**	[0.035, 0.092]	0.241**	[0.162, 0.319]	0.108**	[0.057, 0.158]
Controls		YES		YES		YES		YES		YES		YES		YES	
Observations		570		570		570		570		570		570		570	
Regions (NUTS2)		41		41		41		41		41		41		41	
Model fit indices															
NFI		1.000		1.000		1.000		1.000		1.000		1.000		1.000	
NNFI		1.000		1.000		1.000		1.000		1.000		1.000		1.000	
TLI		1.000		1.000		1.000		1.000		1.000		1.000		1.000	
CFI		0.666		0.693		0.622		0.618		0.894		0.606		0.923	
RMSEA		0.000		0.000		0.000		0.000		0.000		0.000		0.000	
SRMR		0.029		0.028		0.024		0.022		0.025		0.023		0.023	
RFI		1.000		1.000		1.000		1.000		1.000		1.000		1.000	

Notes: Significance levels: *** p<0.01, ** p<0.05, * p<0.1. X differs in each of the hypotheses and represents the variable of interest in each hypothesis. Controls: Regional population density and Krugman specialisation index For each index, an acceptable level of fit is indicated as follows: CFI >0.95; NFI > 0.95; NNFI > 0.95; RMSEA < 0.05; RFI > 0.90; SRMR < 0.08.

Table A2 Mediation of the effect of BERD on UKRI projects/grants and regional economy convergence (2-year later) – Full model linked to Table 10

		H1a		**H1b**		**H2a**		**H2b**		**H2c**		**H3a**		**H3b**	
		Regional projects		**Regional grants**		**Intraregional coll.**		**Interregional coll.**		**Diversified Know. Coll.**		**Coll with London projects**		**Coll. with London grants**	
		Estimate	**95% CI**	**Estimate**	**95% CI**	**Estimate**	**95% CI**	**Estimate**	**95% CI**	**Estimate**	**95% CI**	**Estimate**	**95% CI**	**Estimate**	**95% CI**
Within-region															
BERD ~ X	(path a)	0.020	[-0.026, 0.067]	-0.005	[-0.035, 0.026]	0.033+	[-0.001, 0.066]	0.046*	[0.005, 0.086]	0.006	[-0.007, 0.020]	0.033	[-0.016, 0.081]	-0.006	[-0.015, 0.004]
GDP ~ BERD	(path b)	-0.492	[-1.133, 0.149]	-0.476	[-1.117, 0.164]	-0.463	[-1.107, 0.180]	-0.425	[-1.067, 0.217]	-0.478	[-1.120, 0.164]	-0.463	[-1.105, 0.179]	-0.488	[-1.130, 0.154]
GDP ~ X	(path c)	0.146	[-0.201, 0.494]	0.139	[-0.090, 0.369]	-0.088	[-0.344, 0.167]	-0.284	[-0.592, 0.024]	-0.015	[-0.119, 0.088]	-0.185	[-0.550, 0.181]	-0.014	[-0.084, 0.057]
Indirect effect	(a*b)	-0.010	[-0.036, 0.016]	0.002	[-0.013, 0.017]	-0.015	[-0.041, 0.011]	-0.019	[-0.053, 0.015]	-0.003	[-0.011, 0.005]	-0.015	[-0.046, 0.016]	0.003	[-0.003, 0.009]
Total effect	(c + ab)	0.136	[-0.212, 0.484]	0.142	[-0.088, 0.371]	-0.103	[-0.359, 0.152]	-0.303	[-0.610, 0.003]	-0.018	[-0.122, 0.085]	-0.200	[-0.565, 0.166]	-0.011	[-0.082, 0.060]
Between-region															
BERD ~ X	(path a)	1.323***	[0.981, 1.665]	0.770***	[0.523, 1.017]	0.728***	[0.435, 1.021]	1.113***	[0.824, 1.401]	0.314***	[0.199, 0.428]	1.139***	[0.831, 1.447]	0.599***	[0.413, 0.785]
GDP ~ BERD	(path b)	-0.037	[-0.465, 0.391]	0.057	[-0.304, 0.418]	-0.061	[-0.355, 0.232]	-0.034	[-0.439, 0.372]	0.033	[-0.294, 0.359]	0.057	[-0.336, 0.450]	0.015	[-0.488, 0.518]
GDP ~ X	(path c)	0.528	[-0.208, 1.265]	0.239	[-0.161, 0.639]	0.520	[0.170, 0.870]	0.453	[-0.135, 1.040]	0.132	[-0.026, 0.290]	0.309	[-0.283, 0.902]	0.190	[-0.220, 0.601]
Indirect effect	(a*b)	-0.048	[-0.616, 0.519]	0.044	[-0.234, 0.322]	-0.045	[-0.260, 0.171]	-0.037	[-0.489, 0.414]	0.010	[-0.092, 0.113]	0.065	[-0.382, 0.512]	0.009	[-0.292, 0.310]
Total effect	(c + ab)	0.480**	[0.061, 0.898]	0.283**	[0.012, 0.554]	0.475**	[0.206, 0.745]	0.416**	[0.065, 0.766]	0.142**	[0.026, 0.258]	0.374**	[0.004, 0.744]	0.199	[-0.010, 0.408]
Controls		YES		YES		YES		YES		YES		YES		YES	
Observations		570		570		570		570		570		570		570	
Regions (NUTS2)		41		41		41		41		41		41		41	
Model fit indices															
NFI		1.000		1.000		1.000		1.000		1.000		1.000		1.000	
NNFI		1.000		1.000		1.000		1.000		1.000		1.000		1.000	
TLI		1.000		1.000		1.000		1.000		1.000		1.000		1.000	
CFI		0.911		0.888		0.901		0.899		0.901		0.903		0.911	
RMSEA		0.000		0.000		0.000		0.000		0.000		0.000		0.000	
SRMR		0.029		0.028		0.025		0.023		0.025		0.024		0.029	
RFI		1.000		1.000		1.000		1.000		1.000		1.000		1.000	

Notes: Significance levels: *** p<0.01, ** p<0.05, * p<0.1. X differs in each of the hypotheses and represents the variable of interest in each hypothesis. Controls: Regional population density and Krugman specialisation index For each index, an acceptable level of fit is indicated as follows: CFI >0.95; NFI > 0.95; NNFI > 0.95; RMSEA < 0.05; RFI > 0.90; SRMR < 0.08.

Table A3. Mediation of the effect of BERD on UKRI projects/grants and regional economy prosperity (measured as GDP per head 4-year later)

		H1a		H1b		H2a		H2b		H2c		H3a		H3b	
		Regional projects		Regional grants		Intraregional coll.		Interregional coll.		Diversified Know. Coll.		Coll with London projects		Coll. with London grants	
		Estimate	**95% CI**	**Estimate**	**95% CI**	**Estimate**	**95% CI**	**Estimate**	**95% CI**	**Estimate**	**95% CI**	**Estimate**	**95% CI**	**Estimate**	**95% CI**
Within-region															
BERD ~ X	(path a)	0.020	[-0.026, 0.067]	-0.005	[-0.035, 0.026]	0.033+	[-0.001, 0.066]	0.046*	[0.005, 0.086]	0.006	[-0.007, 0.020]	0.033	[-0.016, 0.081]	-0.006	[-0.015, 0.004]
GDP ~ BERD	(path b)	-0.008	[-0.020, 0.003]	-0.005	[-0.018, 0.007]	-0.008	[-0.021, 0.004]	-0.009	[-0.022, 0.004]	-0.007	[-0.020, 0.006]	-0.007	[-0.020, 0.006]	-0.005	[-0.018, 0.007]
GDP ~ X	(path c)	0.036	[0.029, 0.042]	0.012	[0.008, 0.017]	0.012	[0.007, 0.017]	0.016	[0.010, 0.022]	0.005	[0.003, 0.007]	0.012	[0.005, 0.020]	0.001	[0.000, 0.002]
Indirect effect	(a*b)	0.000	[-0.001, 0.000]	0.000	[0.000, 0.000]	0.000	[-0.001, 0.000]	0.000	[-0.001, 0.000]	0.000	[0.000, 0.000]	0.000	[-0.001, 0.000]	0.000	[0.000, 0.000]
Total effect	(c + ab)	0.035**	[0.029, 0.042]	0.012**	[0.008, 0.017]	0.012**	[0.007, 0.017]	0.015**	[0.009, 0.021]	0.005**	[0.003, 0.007]	0.012**	[0.005, 0.019]	0.001**	[0.000, 0.002]
Between-region															
BERD ~ X	(path a)	1.323***	[0.981, 1.665]	0.770***	[0.523, 1.017]	0.728***	[0.435, 1.021]	1.113***	[0.824, 1.401]	0.314***	[0.199, 0.428]	1.139***	[0.831, 1.447]	0.599***	[0.414, 0.785]
GDP ~ BERD	(path b)	0.095*	[0.008, 0.183]	0.123**	[0.048, 0.198]	0.117***	[0.054, 0.181]	0.123**	[0.038, 0.208]	0.132***	[0.063, 0.201]	0.094*	[0.016, 0.172]	0.132*	[0.027, 0.237]
GDP ~ X	(path c)	0.148	[-0.003, 0.299]	0.065	[-0.018, 0.148]	0.092	[0.016, 0.167]	0.079	[-0.045, 0.202]	0.024	[-0.009, 0.058]	0.141	[0.023, 0.259]	0.033	[-0.053, 0.118]
Indirect effect	(a*b)	0.126**	[0.007, 0.245]	0.095**	[0.030, 0.159]	0.086**	[0.029, 0.142]	0.137**	[0.036, 0.237]	0.041**	[0.015, 0.068]	0.107**	[0.014, 0.200]	0.079**	[0.013, 0.145]
Total effect	(c + ab)	0.274**	[0.181, 0.367]	0.16**	[0.096, 0.224]	0.177**	[0.110, 0.245]	0.216**	[0.133, 0.298]	0.066**	[0.037, 0.095]	0.248**	[0.168, 0.327]	0.112**	[0.061, 0.163]
Controls		YES		YES		YES		YES		YES		YES		YES	
Observations		570		570		570		570		570		570		570	
Regions (NUTS2)		41		41		41		41		41		41		41	
Model fit indices															
NFI		1.000		1.000		1.000		1.000		1.000		1.000		1.000	
NNFI		1.000		1.000		1.000		1.000		1.000		1.000		1.000	
TLI		1.000		1.000		1.000		1.000		1.000		1.000		1.000	
CFI		0.629		0.642		0.541		0.511		0.889		0.493		0.920	
RMSEA		0.000		0.000		0.000		0.000		0.000		0.000		0.000	
SRMR		0.031		0.029		0.026		0.023		0.026		0.024		0.024	
RFI		1.000		1.000		1.000		1.000		1.000		1.000		1.000	

Notes: Significance levels: *** $p<0.01$, ** $p<0.05$, * $p<0.1$. X differs in each of the hypotheses and represents the variable of interest in each hypothesis. Controls: Regional population density and Krugman specialisation index For each index, an acceptable level of fit is indicated as follows: CFI >0.95; NFI > 0.95; NNFI > 0.95; RMSEA < 0.05; RFI > 0.90; SRMR < 0.08.

Table A4. Mediation of the effect of BERD on UKRI projects/grants and regional economy convergence (4-year later)

		H1a Regional projects		H1b Regional grants		H2a Intraregional coll.		H2b Interregional coll.		H2c Diversified Know. Coll.		H3a Coll with London projects		H3b Coll. with London grants	
		Estimate	**95% CI**	**Estimate**	**95% CI**	**Estimate**	**95% CI**	**Estimate**	**95% CI**	**Estimate**	**95% CI**	**Estimate**	**95% CI**	**Estimate**	**95% CI**
Within-region															
BERD ~ X	(path a)	0.020	[-0.026, 0.067]	-0.005	[-0.035, 0.026]	0.033+	[-0.001, 0.066]	0.046*	[0.005, 0.086]	0.006	[-0.007, 0.020]	0.033	[-0.016, 0.081]	-0.006	[-0.015, 0.004]
GDP ~ BERD	(path b)	0.579	[-0.477, 1.635]	0.574	[-0.481, 1.630]	0.558	[-0.501, 1.617]	0.567	[-0.493, 1.627]	0.566	[-0.490, 1.622]	0.545	[-0.511, 1.601]	0.573	[-0.484, 1.630]
GDP ~ X	(path c)	-0.105	[-0.677, 0.467]	0.072	[-0.306, 0.450]	0.068	[-0.353, 0.488]	0.023	[-0.484, 0.531]	0.023	[-0.147, 0.192]	0.263	[-0.338, 0.864]	0.003	[-0.114, 0.120]
Indirect effect	(a*b)	0.012	[-0.023, 0.046]	-0.003	[-0.021, 0.015]	0.018	[-0.021, 0.058]	0.026	[-0.028, 0.079]	0.004	[-0.007, 0.014]	0.018	[-0.026, 0.061]	-0.003	[-0.011, 0.005]
Total effect	(c + ab)	-0.093	[-0.665, 0.479]	0.069	[-0.309, 0.448]	0.086	[-0.334, 0.506]	0.049	[-0.457, 0.555]	0.026	[-0.143, 0.196]	0.281	[-0.320, 0.881]	0	[-0.117, 0.116]
Between-region															
BERD ~ X	(path a)	1.323***	[0.981, 1.665]	0.770***	[0.523, 1.017]	0.728***	[0.435, 1.021]	1.113***	[0.824, 1.401]	0.314***	[0.199, 0.428]	1.139***	[0.831, 1.447]	0.599***	[0.413, 0.785]
GDP ~ BERD	(path b)	-0.143	[-0.836, 0.550]	0.029	[-0.558, 0.615]	-0.123	[-0.602, 0.356]	-0.062	[-0.722, 0.599]	0.035	[-0.499, 0.568]	-0.007	[-0.641, 0.627]	-0.092	[-0.910, 0.726]
GDP ~ X	(path c)	0.956	[-0.237, 2.150]	0.431	[-0.219, 1.081]	0.821	[0.249, 1.392]	0.683	[-0.274, 1.640]	0.201	[-0.057, 0.459]	0.624	[-0.333, 1.581]	0.384	[-0.283, 1.052]
Indirect effect	(a*b)	-0.189	[-1.110, 0.732]	0.022	[-0.429, 0.474]	-0.089	[-0.441, 0.263]	-0.069	[-0.804, 0.667]	0.011	[-0.156, 0.178]	-0.008	[-0.730, 0.714]	-0.055	[-0.547, 0.437]
Total effect	(c + ab)	0.767**	[0.089, 1.445]	0.453**	[0.013, 0.892]	0.731**	[0.290, 1.172]	0.614**	[0.043, 1.185]	0.212**	[0.022, 0.402]	0.616**	[0.020, 1.212]	0.329**	[-0.008, 0.666]
Controls		YES		YES		YES		YES		YES		YES		YES	
Observations		570		570		570		570		570		570		570	
Regions (NUTS2)		41		41		41		41		41		41		41	
Model fit indices															
NFI		1.000		1.000		1.000		1.000		1.000		1.000		1.000	
NNFI		1.000		1.000		1.000		1.000		1.000		1.000		1.000	
TLI		1.000		1.000		1.000		1.000		1.000		1.000		1.000	
CFI		0.943		0.929		0.939		0.938		0.939		0.940		0.943	
RMSEA		0.000		0.000		0.000		0.000		0.000		0.000		0.000	
SRMR		0.031		0.030		0.027		0.025		0.027		0.026		0.031	
RFI		1.000		1.000		1.000		1.000		1.000		1.000		1.000	

Notes: Significance levels: *** p<0.01, ** p<0.05, * p<0.1. X differs in each of the hypotheses and represents the variable of interest in each hypothesis. Controls: Regional population density and Krugman specialisation index

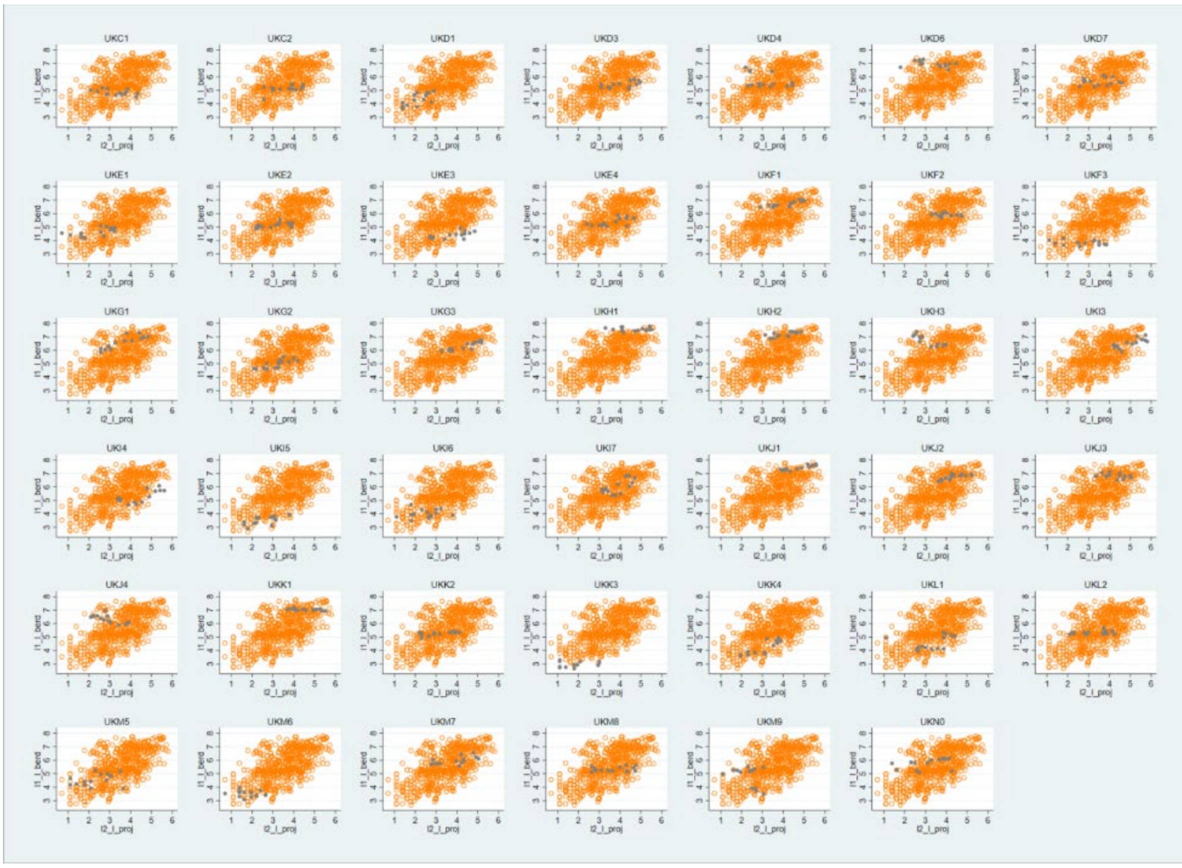

Figure A.1. Association between UKRI regional projects and BERD

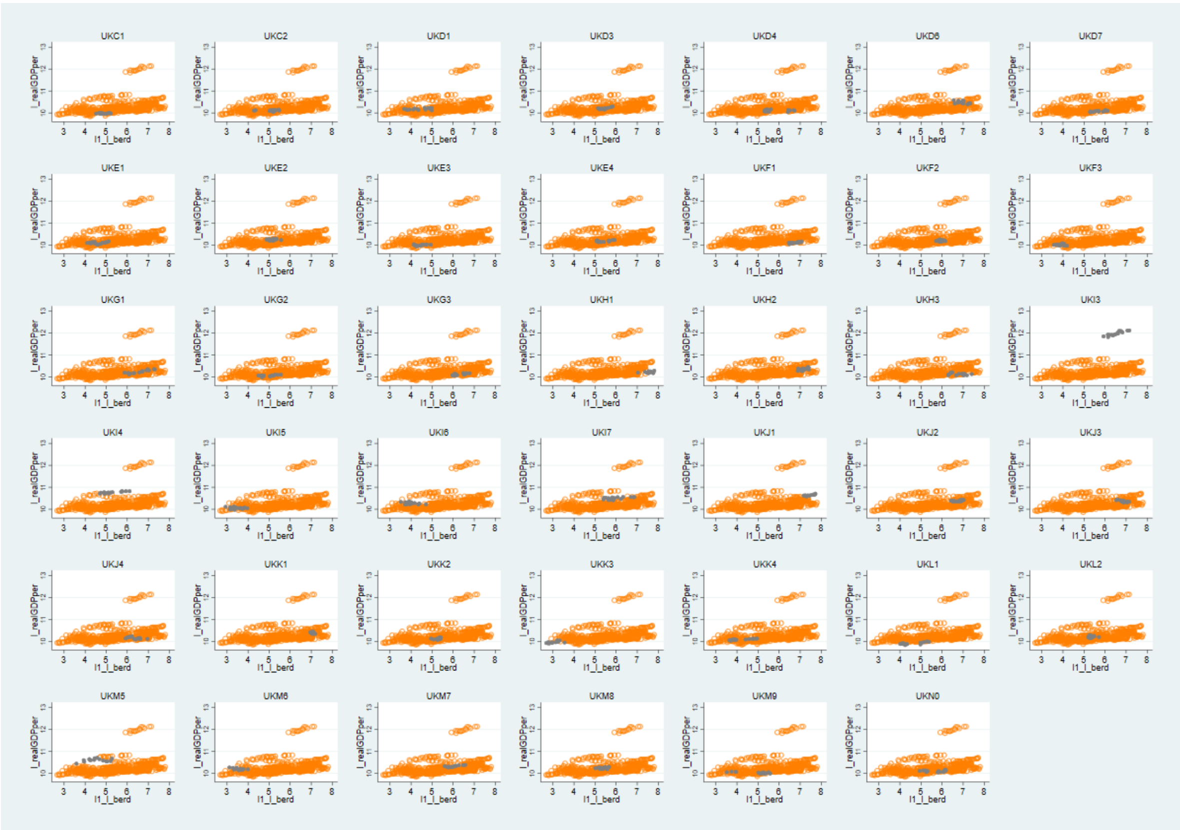

Figure A,2. Association between BERD and regional prosperity (GDP/head)

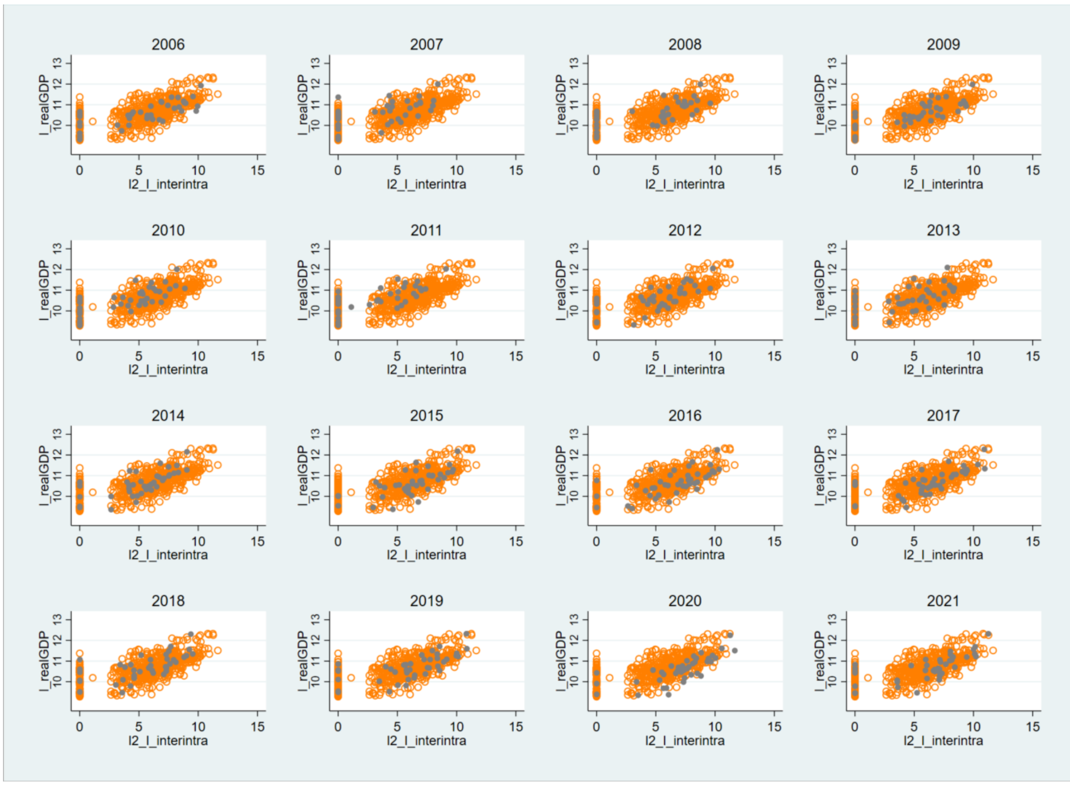

Figure A.3. Scatter plot diversified research collaboration and economic development GDP

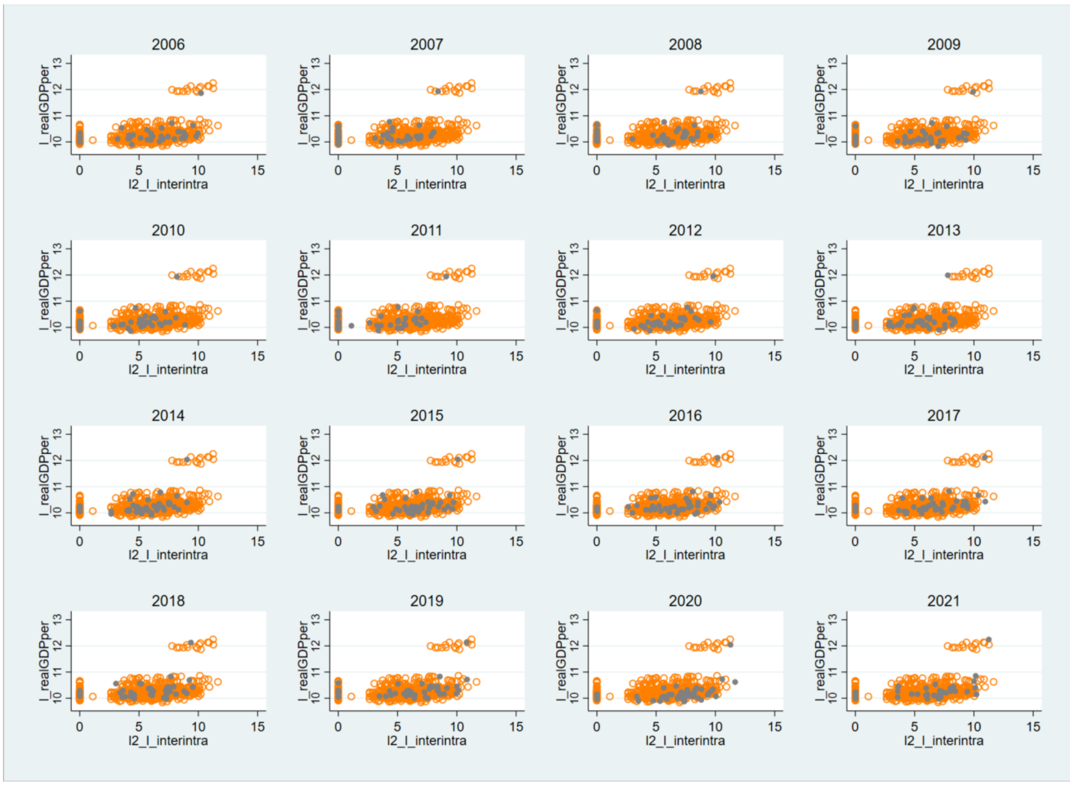

Figure A. 4. Scatter plot diversified research collaboration and regional productivity (GDP/head)

Figure A.5. Diversified Research Collaboration and Economic Prosperity (GDP/head)