

Research Report

Mapping and examining the determinants of England's rural creative microclusters

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NICRE Research Report No 7: May 2022

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Abstract

Creative industries are increasingly being recognised as potential drivers of economic growth in rural areas, and creative industries clusters are one key part of that potential. There is some evidence that these rural clusters have distinct characteristics to those of urban creative clusters, in terms of firms' location decisions as well as configurations of agglomeration and clustering. This study aims to identify the main drivers of clustering of rural creative industries in England, and to compare these drivers to those of clustering in urban settings. This report uses pre-pandemic web scraped data of 184,791 creative industries organisations in England to identify rural creative microclusters of geographically proximate creative firms. Our cluster mapping demonstrates that rural microclusters are widely spread across the country, with about one-third of the rural firms and organisations in our sample are operating in one of the small clusters. Our results for rural clusters are also largely in line with previous findings, which have mainly focused on urban settings and the importance of place-based assets (such as cultural institutions and social capital), location and diverse economies. We find that the drivers of clustering in rural areas are not inherently different from urban areas, apart from a weak link between rural microclustering and informal social networks. This opens avenues for place-based policy making to support microcluster formation and development on the basis of cultural regeneration alongside other forms of economic development. We argue therefore that interventions in 'levelling up' the UK based on creative clusters should champion, rather than exclude, rural creative clusters.

Keywords: Microclusters, rural creative industries, location, agglomeration.

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1. Introduction

Governments across Europe increasingly recognise the economic contribution of rural economies and target rural and peripheral communities' economic growth. In England, rural communities represent 21% of England's population, and contribute about 16% gross value added, (equivalent to about £261 billion), but there is considerable room for growth - up to £347 billion higher than now (Bosworth et al., 2020). Yet, many national policies have historically been 'place blind' (Nurse and Sykes, 2020), or at least have relegated rural areas as a lesser subset of higher-potential towns and cities¹. The concept of 'Left Behind Britain' indicates the existence of pockets of rural life insufficiently served with transport, economic and social infrastructure, education, personal mobility, and health (Cowie et al., 2020; Nurse and Sykes, 2020). The recent 'levelling-up' strategies (National Audit Office, 2022; UK Government, 2022; NICRE, 2021a and b) are aimed to address these 'left behind' areas, but the question that emerges from these strategies is exactly *how* these rural places will catch up. Rural economies have increasingly diversified away from dependency on land-based businesses and there are now a growing range of ways in which creative industries could play a transformative role in economic development in rural areas (Creative Rural Industries Consortium 2019).

The potential for rural creative industries to play a greater role in economic development of rural areas has not received widespread attention, largely due to a longstanding focus on creative clusters in an urban context, both in policy and academic contexts. The creative industries² are well-known to be heavily clustered (i.e., geographically concentrated), but these clusters are often documented in urban areas (Lorenzen and Frederiksen, 2008; Lazzeretti et al., 2008; Berg and Hassink, 2014; Boix et al., 2015). The very large literature on creative clusters (see Bloom et al., 2020 for a review) generally characterises creative industries clusters as an urban phenomenon. This focus on urban creative industries has resulted in the actual and potential contribution of creative industries for the rural and national economy being largely overlooked (Bell and Jayne, 2010; Hill et al., 2022; Roberts and Townsend, 2016), even though there is meaningful evidence that creative enterprises have a significant role to play in rural economies (White 2010; Townsend et al., 2017; Mahon et al., 2018). Others have hinted at the potential for rural creative clusters to be part of a complex, relational ecology of local creatives and cultural infrastructures, igniting an entrepreneurial 'Creative Fire' (Balfour et al., 2018; Harvey et al., 2012). In any case, the development of 'culture economies' based on the valorising of local place-based assets have been a cornerstone of endogenous development models in rural areas, providing opportunities for creative sub-sectors such as arts and crafts to flourish, particularly in remote rural areas (Argent, 2019; Phillip and Williams, 2019; Ray, 2001, 2006).

One reason for the paucity of focus on rural creative industries relates to challenges around availability of and challenges in analysing rurally specific patterns of creative development at small scales (Jones-Hall, 2021; Siepel et al. 2020). One potential mechanism for understanding rural creative industries activity is through creative 'microclusters' (Siepel et al., 2020). These are smaller clusters, which occur both within and without traditional creative clusters and are made up of much smaller groupings of 50 or more proximate creative organisations within a radius of 1 to 5 kilometers. Outside larger creative clusters, companies in microclusters are more likely to grow and to show

¹ In policy terms, cities are seen as engines for growth: '*We will realise our long-term vision for every region and nation to have at least one globally competitive city at its heart to help drive prosperity*' (HM Treasury, 2021: 14)

² In this paper we define creative industries using the DCMS (2014) definition.

appetite for growth (ibid). The potential for understanding creative microclustering in a rural context is significant, as it may provide the evidence basis to understand how rural creative industries are organised and may be supported.

On that basis, this study aims to address this gap by characterising the determinants of microclustering among rural creative industry businesses in England. To characterise the factors driving microclustering, we seek to identify rural microclusters in England, capture differences in composition between microclusters, and compare the drivers of clustering between rural and urban areas.

Our analysis is drawn from data scraped from the websites of 184,791 creative industries organisations in England, from which we were able to extract postcode data of the organisations' locations. Companies were inductively classified into sectors based on activities, and then identified as being in the creative industries using the UK DCMS (2014) definition. We used a density-based clustering method to identify clusters³ of geographically close rural creative firms. We then aggregated the number of firms in microclusters in fine, granular geographies, and estimated a series of regression models to identify the determinants of firms' being based within a microcluster.

Our results show that determinants of microclustering in rural settings are not particularly different from those in urban contexts. We identify 86 rural microclusters, representing 35% of all rural organisations in our sample. From our regression analysis we find relatively few differences between determinants of rural versus urban microclustering. However, we do find that rural microclustering is not associated with informal interactions of people and organisations in the local area.

Our results suggest that microclustering is not only a feature of urban towns and that place-based amenities (culture and social) and diverse and robust industry linkages are strong predictors of such clustering in rural towns and villages. However, the presence of informal networks is not strong enough to explain rural microclustering compared to the process of clustering in urban settings, opening the avenue for policies to encourage the formation of such networks in more rural places (through interventions such as hubs, for instance). We believe that this report helps to understand how rural creative businesses and microclusters may be developed via the UK government's levelling up agenda. We provide policy recommendations to address stark regional differences in creative industries activity and clustering.

The report has the following structure. In section 2 we provide some previous evidence. Section 3 briefly describes the data and the methodology. Section 4 presents and discusses the estimation results. Finally, in Section 5 we conclude.

³ This type of agglomeration represents one type of industrial agglomeration. Regional specialisation is another mechanism suggested in the literature. Our measure captures regions achieving a higher concentration of a particular type of economic activity, regardless of the specific geographical concentration within that region.

2. Literature background: Rural creative industries and creative clustering

The creative industries are widely recognised to be highly clustered, and companies are bound to the places in which they operate (Lazzeretti et al., 2008; Boix et al., 2011; Berg and Hassink, 2014; Bakhshi and Mateos-Garcia, 2016; Scott, 2018; Bloom et al., 2020). Following the work of Alfred Marshall (Marshallian triad), proximity of businesses through clustering is widely understood to produce agglomeration economies, positive externalities arising from business co-location (Gordon & McCann, 2000; Yu, 2020). Agglomeration economies refer to the benefits that companies receive from the concentration in a specific geographic area where suppliers, consumers, competitors, and investors are. Most research on creative clusters tends to consider agglomeration associated with creative clusters as largely urban phenomena, in the process excluding more rural businesses (Harvey et al 2012; Darchen 2016).

The identification of creative clusters as being predominantly urban is at least partially due to the units of analysis in many studies, which are often based on regions, city boundaries or commuting areas (Bloom et al., 2020) and tend to foreground larger cities. A steady stream of empirical research has now begun to underscore the importance of micro geographies, which capture agglomeration dynamics at a more refined geographical level (Siepel et al., 2021, 2020; Ozusaglam and Roper, 2021; Rammer et al., 2020). Those studies find that companies that operate in these micro geographies appear to have characteristics associated with agglomeration economies (for instance innovation, competitiveness, and productivity), wherever they are – regardless of whether they are in urban or non-urban settings. For instance, Siepel et al (2020, 2021) find that companies in creative 'microclusters' outside of established, large clusters are more likely to show traditional characteristics of 'clustered' firms and are more likely to aim for growth.

If clusters are understood to be important, then what factors are associated with the formation of these clusters? Early studies, which depart from the contributions of Florida (2002) on the location of the creative class, show that drivers of clustering range from labour market conditions, such as skills and unemployment, to agglomeration economies, industry specialisation, human capital, and cultural heritage (Lazzeretti, Capone and Boix, 2012; Coll-Martinez and Aruazo-Carod 2018; Coll-Martinez et al., 2019). Yet, many of these studies tend to focus on urban economies, as discussed above. *Do these findings hold in more rural settings?*

2.1 Rural creative industries and creative clustering

The focus of research on creative clusters in an urban context has served in some ways to exclude rural creative firms (Bell and Jayne 2010), but creative industries businesses have a significant role to play in rural economies (White 2010; Townsend 2017; Mahon et al., 2018). At the same time, there is also growing evidence that clustering can be extremely important in rural settings (Harvey et al., 2012; Roberts and Townsend, 2016). Several approaches have been proposed for identifying creative clusters outside urban areas (e.g., Mitchell 2013; Escalona-Orcao et al., 2016).

It does remain unclear the extent to which the emergence of creative clusters in rural areas follows similar patterns to those seen in urban settings. While urban models of creativity-led development such as Florida's Creative Class (Florida, 2012) and Landry's Creative Cities (Landry, 2008) have been critiqued for their exclusion of rural economies (e.g., Miles and Ebury, 2017; Woods, 2012), some studies have suggested that rurally

distinctive variants exist and are important for local development strategies. On this basis, it remains unclear whether place-based assets play a different role in cluster formation than in urban settings. There is established evidence on the importance of institutional factors (cultural and human capital) in the formation of creative firms and the location of clusters (e.g., Cooke and Lazzerati, 2008; Boix et al., 2013; Lazzerati et al., 2013), specifically in the rural context (McGranahan et al., 2010; and Naldi et al., 2021). There is also evidence that suggests that local factors, such as public transport access, infrastructure, and access to natural spaces make locations more attractive (Gottlieb, 1995; House of Lords, 2019, Naldi et al. 2021). For example, there may be a rural 'creative class' linked to the availability of outdoor amenities that persuade creative professionals to trade-off city 'buzz' for rural life (McGrahahan et al., 2011; Verditch, 2010).

One possible mechanism for how rural creative clusters may develop comes through creative hubs. These hubs offer a form of spatial clustering known from urban contexts (Pratt, 2021; Pratt et al., 2019). Many countries have created policies and spaces promoting creative hubs as 'tools' to support creative industries. The fine-tuned view of hubs considers three aspects: the physical co-location of creative industries often in one building, sits next to the operational dimension of short-term contracts for studios for micro-enterprises organised by a hub-manager, allowing for the hub to be a location for informal knowledge exchange and peer support (Hill, 2021; Hill et al., 2022; Merrell and Rowe, 2022; Pratt, 2021).

Beyond these structural factors, there is also limited evidence about the nature of agglomeration economies in rural settings. Two crucial aspects of agglomeration economies relate to industry specialisation and diversity and, more recently, to the concept of related diversity (Franken et al., 2007). The general argument is that knowledge spillovers depend on firms being in close cognitive proximity or relatedness (manifested by the homogeneity of capabilities, skills, and knowledge base) – that is, similar sectors are more likely to have higher knowledge spillovers. This type of proximity is assumed to generate an interactive learning environment where firms can discover, interact, learn, and innovate (Boschma, 2005; Boschma, Balland, & Kogler, 2015; Boschma, 2016). The impact of related diversity on rural settings is still emerging in the literature as opposed to urban settings. Pe'er et al., (2008) and Aharonson et al., (2007) argue that agglomeration economies are prominently present in urban areas. The reasoning behind this argument is that agglomeration economies are positively associated with city size (e.g., Cottineau et al., 2019). Although urban regions may be more likely to host clusters, some scholars argue that rural regions also exhibit agglomeration economies since some rural areas are urbanised or near core urban regions (Naldi et al., 2015). Rural businesses, particularly those in service sectors, have been found to be more innovative where neighbourhoods are diverse in terms of education (Wixe, 2018). Goffette-Nagot and Schmitt (1999) also show that the presence of agglomeration economies in cities induces increasing land rents and finally agglomeration diseconomies. In turn, these diseconomies lead to a decentralisation of firms and jobs, which may relocate close to new consumption centres (where transport costs and office rental costs are lower). Therefore, new spatial patterns appear in the landscape, bringing a new population of firms over time, which will cluster within a certain radius in smaller cities or towns.

Spatial configurations also influence the typology of clusters that operate within urban and rural areas (Goffette-Nagot and Schmitt, 1999). In terms of the size of the clusters, rural clusters may be of a different size given the population density around them and the radius at which they operate. In other words, some clusters may behave as peripheries of large urban areas. The consideration given to the size of clusters and the distance at which they operate raises a few empirical difficulties, which are discussed in section 3.2.

3. Data and methodology

The aim of this study is to better understand the determinants of clustering of rural creative industries (RCI) organisations, and the extent to which these determinants are distinct from those in urban clusters. As a starting point, we aim to generate a bottom-up approach to identifying clusters, agnostic to political or statistical economic boundaries.

3.1 Data

In order to do this, we use data scraped from the websites of 184,791 creative industries organisations, including businesses, charities, and individuals with a web presence in any location in England. The data was scraped by the data analytics company Glass.ai⁴ in 2019. The use of web data to identify creative microclusters has a number of added advantages. Firstly, it helps identify creative sectors that may not be well covered in traditional industrial classifications (SIC codes), which tend to lag behind changes in the economy (the most recent major SIC code revision was in 2007). Creative industries are particularly susceptible to misclassification as their activities, such as virtual/augmented reality, animation, or digital media, do not have distinct SIC codes in the most recent SIC classification. Moreover, while administrative data will hold information on firm location when they were registered, web data has the flexibility to establish the geographic area where the firm is actually based (in that websites need to provide the physical address where customers can find a company).

The activities of the firms were inductively classified into 109 broad sectors based on firms' self-description published on their website. The sectors identified by Glass are distinct from those used in formal SIC codes, which give them broader coverage in sectors that are not always comfortably situated within SIC codes. We therefore manually mapped the 109 broad sectors against the DCMS definition of creative industries, yielding 361,459 websites identifying activities consistent with the DCMS creative industries definition. Of these, 184,791 websites listed a physical address in England, and using addresses and postcodes, these were all geocoded. We then merged the working sample of 184,791 creative firms with the ONS England and Wales Rural classification⁵ (ONS, 2016), allowing us to identify which organisations were located in rural areas.

3.2 Empirical approach

In order to identify rural microclusters we need to:

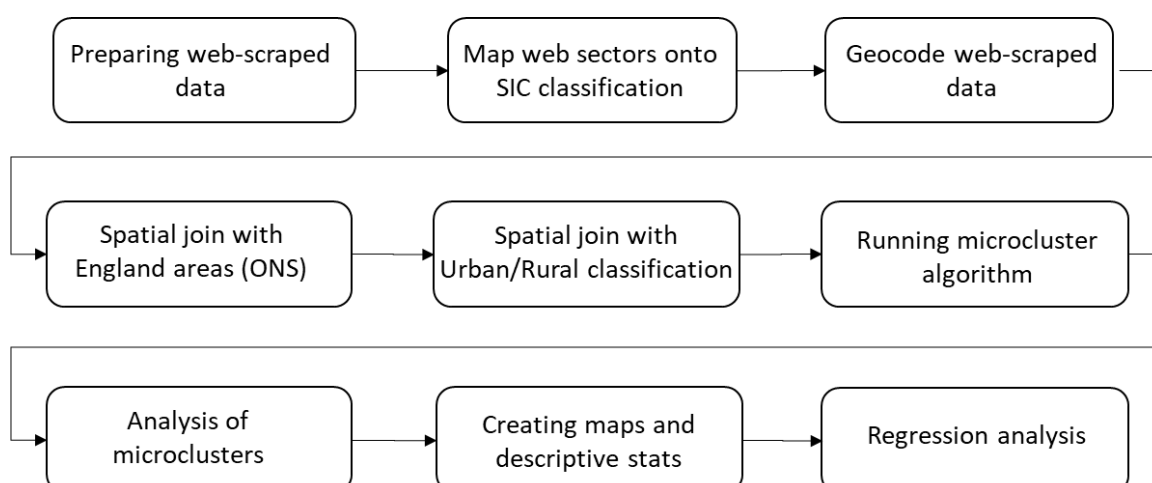
1. Identify creative businesses operating in rural settings
2. Measure the extent to which they are clustered

Figure 1 below outlines the analytical framework for linking web-scraped data with geographical analysis applied in this study. The following steps were taken:

⁴ Data was collected by the data science company Glass.ai. Data is crown copyright. Glass.ai does not bear any responsibility for the analysis or interpretation of the data.

⁵ A rural area falls into settlements with populations of less than 10,000. Two dimensions are used. The first classifies rural settlements based on population densities: and 3 typologies are derived: town and fringe; village; or, hamlet and isolated dwelling. The second dimension relates to the sparsity of population in surrounding areas. Each of the three types of rural areas (as well as 'city and town') are then classified as in a 'sparse setting' or 'not sparse'. See more details: [Guide_to_applying_the_rural_urban_classification_to_data.pdf \(publishing.service.gov.uk\)](#)

Figure 1: Analytical framework for web-scraped data and spatial analysis

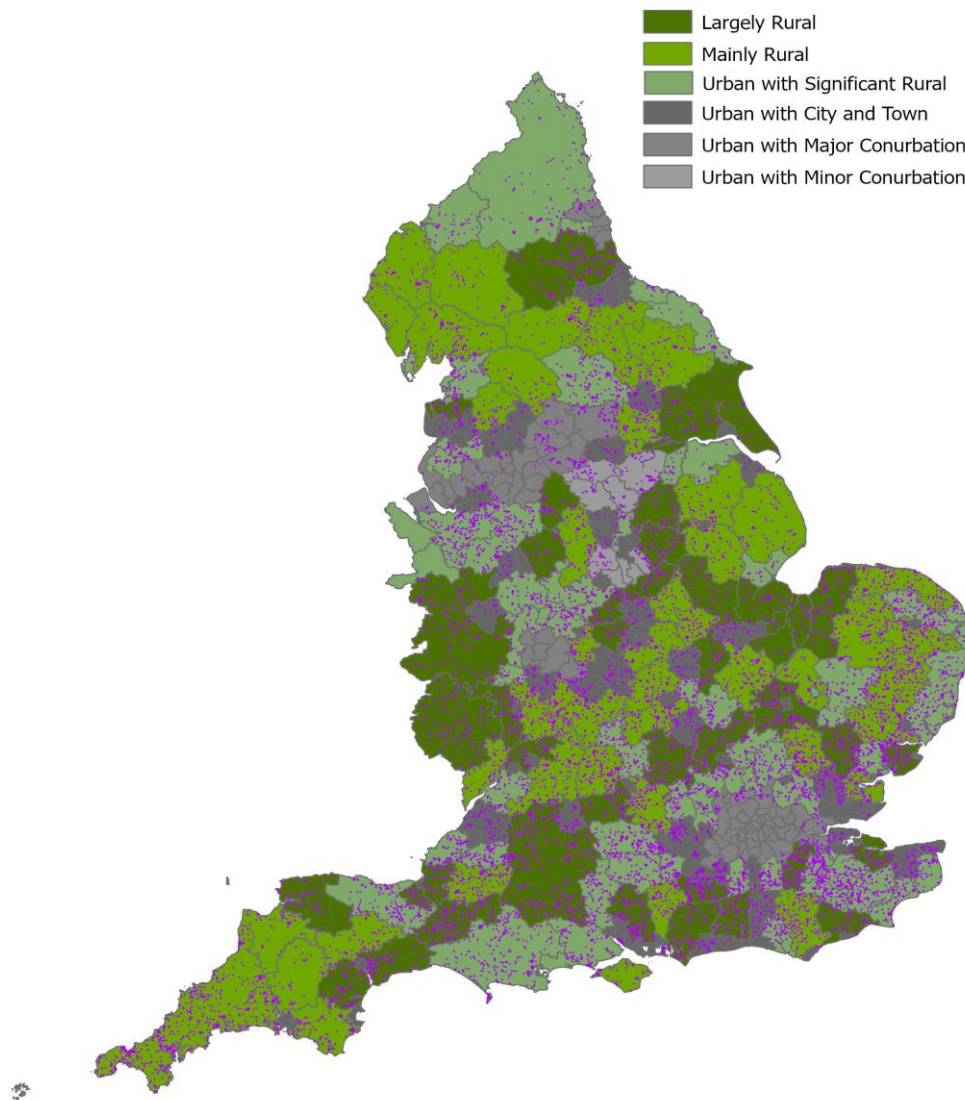


We identified 25,547 companies located in rural settings as characterised by the ONS definition, representing 14% of the total sample. Table 1 reports the distribution of firms by DCMS sub-sector and ONS rural classification, and Figure 1 presents a map of England rural creative firms. About half of the sample firms are located in rural villages and dispersed, and 43% operate within rural towns and fringe.

Table 1. Distribution of rural firms by DCMS sub-sector and RUC classification

ONS rural classification/DCMS sector	Advertising and marketing	Architecture	Crafts	Design	Film, TV video
Rural town and fringe	10.20%	13.60%	9.60%	21.60%	10.60%
Rural town and fringe in a sparse setting	5.70%	9.40%	14.30%	21.20%	10.80%
Rural village and dispersed	10.30%	15.10%	10.60%	20.10%	11.00%
Rural village and dispersed in a sparse setting	5.40%	9.30%	18.70%	18.00%	9.80%
Grand Total	10.00%	14.20%	10.50%	20.70%	10.80%
ONS rural classification/DCMS sector	IT software	Museums	Music performing arts	Publishing	Whole economy
Rural town and fringe	8.40%	4.80%	12.00%	9.00%	42.60%
Rural town and fringe in a sparse setting	3.30%	9.00%	16.10%	10.20%	2.00%
Rural village and dispersed	7.60%	5.00%	11.90%	8.50%	52.60%
Rural village and dispersed in a sparse setting	2.40%	9.70%	16.60%	10.20%	2.80%
Grand Total	7.70%	5.20%	12.20%	8.80%	100.00%

Figure 1. Map of rural creative industries.



Note: Map boundaries correspond to Local Authority Districts in England. Each dot represents one of the 25,547 companies. The categories used within the classification of urban and rural correspond to ONS 2011 Rural-Urban classification of Local Authority Districts in England. Further details: <https://www.gov.uk/government/statistics/2011-rural-urban-classification-of-local-authority-and-other-higher-level-geographies-for-statistical-purposes>

3.3 Mapping rural creative microclusters

The mapping of the creative microclusters is not a trivial task (for a summary of the methods for identifying clusters see Bergman and Feser, 1999). Methods include subjective approaches such as expert opinion and surveys to index base indicators such as location quotients (LQs), concentration indexes or input-output analysis.⁶ More recent applications use spatial statistics in which the analysis of agglomeration puts a great deal of emphasis on space, distance and spatial dependence (van Oort, 2017). Our approach relies on the use of spatial statistics, as these statistics offer some added advantages

⁶ Early exercises study clustering using LQs, for example Florida and Mellander (2008) for the music industry in EU regions; Capone (2008), Lазzerretti et al., (2008) and Boix et al., (2011) for the case of Italy, France, and the UK. For the UK, De Propriis et al (2009) use firm level data.

compared to other methods. Firstly, they induce measurement improvements in the exact definition of agglomeration as the distance becomes more functional in character. Secondly, they offer a finer spatial scale than metropolitan areas (cities, commuting zones, local authorities), shedding more light on intra-urban dependency (Wallsten, 2001; van Oort, 2017).

From the geo-located data, we determined whether a firm is in a microcluster (i.e., a small concentration or group of firms that are relatively close to each other). We implemented a self-adjusting (HDBSCAN) clustering method to detect areas where companies are concentrated and where their location is based in sparse or empty areas. The clustering method employs a machine-learning clustering algorithm to identify a range of distances to separate clusters of varying densities from sparser noise. The algorithm computes hierarchical estimates and scores the outlierness of each data object, extracting local clusters based on a cluster tree.⁷

To identify the threshold of values of what constitutes a 'microcluster', we selected a threshold of 50 firms as the minimum cluster's size. This is the threshold used in previous microcluster studies, including Siepel et al., (2020). This threshold could reasonably capture effects at an immediately proximate area. Looking at the number of neighbours at different radii (Table 2), we see that up to 1000 metres, the average number of neighbours is 14 firms. Up to 5 km, the average number of neighbours is 44. Our threshold of 50 firms per cluster is, therefore, a relatively conservative measure in capturing hotspots of rural firms in a radius of about 1 to 5 km. Table A1 in the appendix shows a summary of a sensitivity analysis that we carried out, testing different threshold measures. We see that while the number of clusters changes, the number of firms in microclusters is relatively the same at different radii.

Table 2: Median count of firms at different radii

Radius (km)	Average count	Median count	Minimum	Maximum
1	14	8	1	62
3	27	23	1	134
5	44	39	1	182
8	78	69	1	272

Note: Hotspot analysis was carried out to estimate the number of neighbours at different distance bands.

Table 3: Firms in clusters by DCMS sector classification

DCMS	Firms in microclusters	Total firms in sample	Per cent firms in microclusters
Advertising and marketing	869	2560	34%
Architecture	1186	3622	33%
Crafts	892	2673	33%
Design	1790	5293	34%
Film, TV, video, radio and photography	928	2761	34%
IT, Software, video games ^a	834	1969	42%

⁷ For further details on the cluster method see Campello, Moulavi, and Sander (2013).

Museums, galleries and libraries	362	1319	27%
Music & performing arts ^b	995	3104	32%
Publishing and translation	724	2246	32%
Grand total	8,580	25,547	34%

Notes: ^a Subsector also includes computer services; ^b subsector also includes visual arts and cultural education

Through the application of the density-based clustering method, we identified 86 rural creative microclusters across England (see Tables 2 and 3). Overall, about 34% of firms in the sample are in a microcluster. The fraction of firms in microclusters by DCMS varies across sectors 'IT software' represents the most clustered sub-sector. Figure 1 displays the clusters identified.

By region, the North West, North East and East of England have the most significant proportion of rural firms operating in microclusters. Regarding the ONS rural typologies, about 60% of the microclusters are located in rural towns and fringes, and 40% work in rural villages not in sparse settings (see Table 3). Looking at the microclusters map, we can see that some clusters are on the periphery of large cities as those surrounding London, Manchester, or Birmingham.

Table 3. Percentage of firms in microclusters by NUTS-1 and ONS rural classification

NUTS-1/RUC11	Rural town and fringe	Rural town and fringe in a sparse setting	Rural village and dispersed	Rural village and dispersed in a sparse setting	Share of total sample
East Midlands	64%	0%	36%	0%	9.6%
East of England	53%	1%	46%	0%	20.2%
London	50%	0%	50%	0%	0.1%
North East	83%	0%	17%	0%	2.6%
North West	33%	7%	59%	1%	6.9%
South East	60%	0%	40%	0%	24.9%
South West	50%	4%	43%	3%	20.4%
West Midlands	40%	0%	60%	0%	7.9%
Yorkshire and The Humber	66%	9%	21%	4%	7.3%
Whole economy	53%	2%	44%	1%	

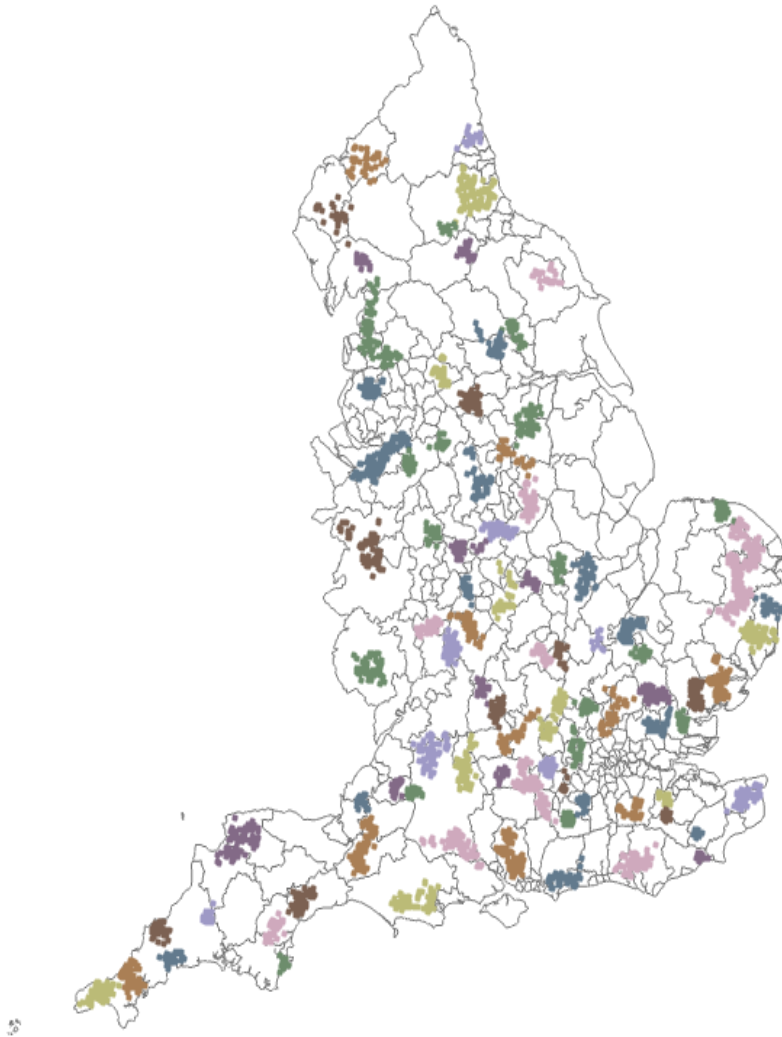
Table 4. Percentage of firms in microclusters by NUTS-1 and DCMS sectors (as a proportion of all rural firms)

NUTS-1/DMCS	Advertising and marketing	Architecture	Crafts	Design	Film, TV video
East Midlands	30%	29%	31%	30%	31%
East of England	38%	32%	37%	33%	34%
London	25%	0%	0%	10%	50%
North East	38%	43%	31%	45%	37%
North West	64%	67%	66%	70%	64%

South East	32%	29%	31%	29%	31%
South West	25%	28%	26%	30%	25%
West Midlands	32%	36%	32%	34%	38%
Yorkshire and The Humber	31%	29%	28%	29%	34%
Whole economy	34%	33%	33%	34%	34%

NUTS-1/DMCS	IT Software	Museums	Music performing arts	Publishing
East Midlands	39%	27%	29%	34%
East of England	43%	33%	33%	30%
London	100%	0%	50%	0%
North East	46%	30%	51%	47%
North West	77%	51%	54%	60%
South East	40%	23%	30%	29%
South West	35%	20%	27%	28%
West Midlands	40%	25%	30%	33%
Yorkshire and The Humber	41%	23%	30%	25%
Whole economy	42%	27%	32%	32%

Figure 2. Map of microclusters identified



Note: Map boundaries correspond to local authority districts in England. Each colour represents a visually distinct cluster

3.4 Regression analysis

With the mapping complete, the next step is to identify the determinants of clustering. We estimate a set of regression models intending to analyse how certain local factors are associated with the location of rural-urban creative microclusters.

Dependent variable

We sum the number of creative firms in microclusters across a Lower Super Output Area (LSOA). The sum corresponds to the total number of firms in microclusters at each LSOA within 1 Km². Lower Super Output Areas (LSOA) are a census dissemination unit that represents homogeneous neighbourhoods of 1,500 residents on average, and are the smallest geographical unit used by the ONS. Using LSOA as a measure has the advantage of capturing microclustering dynamics at a very granular level (i.e., close to a

neighbourhood) whilst offering the opportunity to use boundaries and centroids to aggregate headcount information at a radius of 1km of the LSOA to construct our control variables.⁸ Previous empirical analyses also show that creative firms only benefit from localisation economies within the first kilometre (Arzaghi and Henderson, 2008; Coll-Martinez et al., 2019; Coll-Martinez, 2019). For estimation purposes, the variable is transformed into logarithmical form (*log_stock*).

Explanatory variables

Our interest in this empirical exercise is to test the role of different types of location-based amenities and the learning aspect of agglomeration economies with a focus on rural creative microclusters. Our selection of explanatory variables draws on prior studies of creative industries location and general firm location studies. We geocoded data from several databases to identify the following set of regressors:

- i) Neighbourhood supply of cultural amenities: Cultural amenities include museums, public galleries, heritage sites, libraries, archives, and science centres. They have been found to have important implications for creativity and local economic development (Knudsen et al., 2008; Cooke and Lazzarretti, 2008; Bakhshi, Lee and Mateos-Garcia, 2014). Cultural amenities are also geographical-specific identities and could explain differences in business operation between urban and rural settings (Malecki, 1993). We calculated the number of cultural institutions covered for each LSOA within 1Km² (*ln_cultural_inst*). The data⁹ covers 11,304 listings, for which 10,571 places were geocoded and merged to our main data.

The supply of a cultural landscape can also induce local social capital, which refers to the local cultural and creative industry related networks (Naldi et al., 2021). Public spaces allow information to circulate and exchange as well as providing an opportunity for firms to generate a sense of community belonging (Andres and Round, 2015). Those interactions mainly take place through informal connections through social networks, fairs, and venues. To account for this, we consider the number of organisations dedicated to exhibitions, campaigns and initiatives, festivals, cultural and scientific meetings by LSOA.¹⁰

- ii) Neighbourhood supply of nature-based amenities: place-bound resources provide access to scarce (Marcoullier and Clendenning, 2005), immobile (Power, 2005), and irreproducible resources that firms may exploit if they locate nearby. Naldi et al. (2021), for instance, show that both urban and rural firms derive a positive benefit from natural amenities such as natural areas and parks. However, these types of amenities are more important in rural areas than in urban areas. Moreover, evidence in Verditch (2010) and McGranahan et al., (2011) suggests that nature-based amenities may be attractive for a rural 'creative class,' which might drive collocation of creative industries businesses.

⁸ There are 34,753 LSOA in England and Wales. While full dataset contains this number of LSOA, some of the crucial control variables that we employ in our models are not available for all LSOA. Therefore, in subsequent analyses we present data on the sample of LSOA for which information on all relevant variables is available.

⁹ Data was drawn from Culture24, a private organization that operates in the UK and has the rights of the most complete data of cultural amenities available in the country. We thank Culture24 for providing an API to access the data. Culture24 does not bear any responsibility for the analysis of the data.

¹⁰ Data also collected from Culture24. See footnote 9 for further details.

To test this, our measure of nature-based amenities (*ln_nature*) summarises the number of gardens, environmental and ecological centres, national parks and areas of outstanding natural beauty for each LSOA.

- iii) Local knowledge environment and local labour pool: Many universities and colleges cooperate with local businesses to ensure their offerings meet the skills needs of their respective region. Valero and Van Reenen (2019) also show a positive spillover effect from universities to their closest neighbouring regions. These institutions may also be a source of ideas or cultural amenities (Combes, Duranton and Gobillon, 2010). To capture the local knowledge environment, we control for the number of universities and colleges within each LSOA (*log_universities*, *log_colleges*). For robustness check, we also employ a distance measure (in kms) of the LSOA to the nearest higher education institution.
- iv) Agglomeration spillovers: Evolutionary Economic Geography (EEG) argues that cognitive proximity, as well as geographical proximity, are important in the flow of knowledge through regions (Boschma and Martin, 2007). Drawing on this notion, we introduce three measures usually applied in the empirical literature on industrial location. First, we control for the industry composition by computing two diversity indexes of all industry sectors at the LSOA, following Frenken et al., (2007), and Wixe and Andersson (2017) 's approach. The first index refers to unrelated diversity (*UD*), which determines the extent to which firms operate in different industries that share several similarities within the local area. Operationally, UD measures the distribution of employees in the neighbourhood between 2-digit industries.¹¹ The second index, related diversity (*RD*), captures the extent to which firms operate in different industries that share few or limited similarities (Frenken et al., 2007). The index measures the distribution of employees between 5-digit industries within each 2-digit sector. The concepts of related diversity and unrelated diversity reflect the level of regional/local specialisation: a low level of regional specialisation could be an indication of a high level of related or unrelated industrial diversity (Aastad et al., 2016)¹²

The third measure captures neighbourhood specialisation using employment-based location quotients at the LSOA. Location quotients are computed for creative industries, manufacturing, services-based activities and knowledge-based activities (e.g., Cruz and Teixeira, 2021; Arauzo et al., 2010; Lazzaretto et al., 2013).

We also try to control for the presence of agglomeration and urbanisation economies. We first use population density (*ln_pop*) as densely populated areas display more interactions between economic agents (Rodríguez-Pose and Hardy, 2015). We measure population density as the number of inhabitants per km² at the LSOA.¹³ Second, we control for the affordability of local offices and spaces, which is also considered a proxy for agglomeration economies (Drennan and Kelly, 2011; Andres and Round, 2015; Santos Cruz

¹¹ We use the Standard Industrial Classifications (SIC). Employment data obtained from the business register data available on the NOMIS platform.

¹² The measures we employ in this paper are not the only ones that can capture related/unrelated variety. Existing measures also include co-occurrence of products within firms, input-output linkages, and the intensity of labour relocation (Boschma and Gianelli, 2014)

¹³ Data drawn from [ONS Lower layer Super Output Area population density \(National Statistics\) - Office for National Statistics \(ons.gov.uk\)](https://ons.gov.uk)

and Teixeira, 2021).¹⁴ The rateable value per m² at the LSOA is used as a control variable (*ln_rate*). Another control refers to the distance of each LSOA to the main city (*distance2city*). For this purpose, we use the major towns and cities statistical geography, which provides a precise definition of the most important cities and towns in England.¹⁵ Being closer to a core city or area may bring potential economic size benefits (Hanson, 2001; Marcon and Puech, 2003). Furthermore, to account for regional economic aspects that can drive clustering we control for the level of unemployment at the district level.¹⁶ As shown by Duranton and Puga (2004) and Glaeser et al. (2015), firms prefer to locate in areas with enough workers.¹⁷

For estimation purposes, the reference period for our dependent variable is the year 2019, whereas all explanatory variables are the years 2018 and 2017, where possible, to avoid problems of simultaneity. We also include dummies for the commuting hinterland where most people work (also known as travel-to-work areas, TTWA). The data we use is mainly cross-sectional, reducing the possibility of controlling for sources of endogeneity. For instance, the location patterns of creative microclusters could be explained by the innovativeness embedded in places and regions. As we discuss above, we control for the presence of universities and colleges as a means of controlling for possible knowledge or innovation spillovers arising from universities. Despite this, knowledge spillovers can come from different sources, for instance, dominant technologies being developed in the region, or innovation hubs that attract and support cultural organisations or creative businesses. Notwithstanding, the nature of our key variables makes the use of time variation redundant to some extent, as nature and culture-based amenities hardly change over time (time-invariant).

Two samples are used to estimate models. The first sample corresponds to 4,702 rural areas located in England. The second sample covers 18,765 urban areas. We separate these two samples to investigate the reasons for apparent differences in creative microcluster location in rural and urban areas. Table 3 displays the variables used and summary statistics. The distribution of our dependent variable (*stock*) has two features that are worthy of attention. First, the variance is larger than the mean, implying that the data is over-dispersed. In addition, the variable refers to the number (or count) of firms in microclusters. For these reasons, we estimate a Negative Binomial regression (NBR), which can model the dispersion by adding an extra parameter into the model. The NBR is a generalisation of Poisson regression. Table A3 in the appendix reports a correlation matrix. None of the correlations reported appears to be particularly high.¹⁸

¹⁴ Data obtained from the Evaluation Office Agency in the UK. For further information on the methodology: [here](#)

¹⁵ This data, drawn from the ONS, corresponds to 112 major towns and cities in England and Wales. The ONS used a population size threshold of 75,000 usual resident population or workday population to define these cities as at 2011 Census.

¹⁶ There are a total of 309 districts in England. They are a level of subnational division of England and determine the structure of local governments.

¹⁷ Data obtained from the Annual Population Survey (2018); population data corresponds to 2018 mid-year population estimates by ONS.

¹⁸ Variance inflation factors are below the threshold of 9, providing no indication of strong multicollinearity.

Table 5. Descriptive statistics of main variables

Var	Description	Rural=4,702				Urban= 18,765			
		Mean	Std. Dev.	Min	Max	Mean	Std. Dev.	Min	Max
<i>Dependent variable</i>									
Stock	Stock of firms in microclusters (#)	1.57	4.64	0	66	2.88	14.83	0	699
<i>Amenities</i>									
cultural_inst	Number of cultural institutions within 1Km ²	.45	1.01	0	11	1.1	1.45	0	47
ln_cultural_inst	Cultural institutions within 1Km ² (log)	.24	.45	0	2.48	.16	.42	0	3.87
Social k	Number of social organisations within 1Km ² (#)	.07	.27	0	4	.07	.37	0	12
ln_socialk	Social organisations (log)	.05	.18	0	1.61	.04	.19	0	2.56
Nature	Number of nature-based amenities within 1Km ² (#)	.29	.63	0	8	.08	.3	0	6
ln_nature	Nature based amenities within 1Km ² (log)	.18	.35	0	2.2	.05	.19	0	1.95
Universities	Number of universities within 1Km ² (#)	0	.03	0	1	0	.07	0	3
ln_universities	Universities within 1Km ² (log)	0	.02	0	.69	0	.05	0	1.39
Colleges	Number of Colleges within 1Km ²	0	.06	0	1	.02	.13	0	3
ln_colleges	Colleges within 1Km ² (log)	0	.04	0	.69	0	.07	0	3
<i>Agglomeration, industry, and size</i>									
RD	Related diversity	.33	.18	-.14	1.13	.33	.23	-.08	1.22
UD	Unrelated diversity	2.37	.44	.23	3.32	2.07	.55	0	3.44
LQ cis	Location quotient of creative industries	.87	1.27	0	22.85	1.08	1.67	0	28.14
LQ serv	Location quotient of services-based industries	.89	.25	0	1.42	.94	.31	0	1.57
LQ manuf	Location quotient of manufacturing industries	1.37	1.08	0	6.98	.98	1.07	0	7.13
LQ know	Location quotient of knowledge-based activities	1.24	1.43	0	9.03	1.54	2.17	0	11.09
Pop	People per square km	1639.2	337.51	995	2741	1625.5	264.9	983	2737
ln_pop	People per square km (log)	4	7.38	.2	6.9	7.38	.16	6.89	7.91
Unemp	Unemployment rate (%)	3.49	.94	2	7.9	4.57	1.39	2	8.6
distance2city	Distance to the major town/city kms)	16.22	14.87	0	110.63	4.61	10.13	0	101.59

Var	Description	Rural=4,702				Urban= 18,765			
		Mean	Std. Dev.	Min	Max	Mean	Std. Dev.	Min	Max
distance2city	Distance to the major town/city (log)	2.51	.85	0	4.72	.85	1.17	0	4.63
Rate	Office rateable value per m ² (£)	52.56	26.75	7	342	87.95	55.87	0	427
ln_rate	Office rateable value per m ² (log)	3.88	.44	2.08	5.84	4.32	.58	0	6.06

Note: Table A2 in the appendix provides further definitions of these variables.

4. Results

4.1 Rural vs Urban determinants of microclustering

We present the results of estimating models by using two different sub-samples, split by rural and urban location (Table 6). For each sample, we evaluate four separate models, testing different specifications. Overall, results are generally robust across all estimations (i.e., coefficients do not change markedly when adding additional controls). Estimations in columns 4 and 8 do not include population density (\ln_pop), as this variable is highly correlated with the measures associated with related and unrelated diversity (RD and UD, respectively). We also tested non-linear effects for the office rateable value per m² (\ln_rate). The interpretation that follows is based on our preferred specification displayed in columns 4 and 8.

Regarding our main explanatory variables, the regressions show a positive sign for cultural amenities when the model is estimated using both sub-samples. This result corroborates the fact that provision of culture-associated activities is an essential aspect in the dynamics of creative microclusters in urban areas and rural ones. In other words, the accumulation of culturally led facilities could stimulate clustering, providing a common resource base that brings identity and aesthetic values (Throsby 2008). These results are parallel to those of Lazeretti, Capone and Boix (2012) for Italian urban areas, where the presence of cultural and artistic heritage influences the presence of heritage-dependent creative industries.

Interestingly, we find some differences between rural and urban areas regarding the provision of local knowledge. Universities play an important role in microclusters in rural and urban areas. The coefficient associated with the log of universities is positive and statistically significant. This means that universities in rural regions exercise an attractive attraction pole that promotes the agglomeration of creative industries; and perhaps that staff/students at these institutions are active in business offering creative services. For FE colleges, which are highly heterogeneous in England in terms of levels of instruction, topics covered, and location, the results are mixed. While the number of FE colleges in the neighbourhood is positive and significantly associated with microclusters in urban areas, it tends to be insignificant in rural areas.¹⁹ This is likely explained by the location of these colleges – many FE colleges in rural areas are themselves located in highly rural settings where co-location with any businesses, creative or non-creative, may be hindered by geography²⁰. As such a colocation effect might be expected to take place over a wider geographical area, as our evidence in the following section suggests. The finding also raises the question of how rural creative businesses are connected with local colleges and whether these institutions provide resilience for the location of creative businesses. We explore this issue in more detail in the next section.

We do not see a difference between rural and urban settings regarding nature-based amenities and social capital. For the former, there is no significant association between the supply of nature-based amenities in both samples. Concerning the role of social capital, results show that this variable is positively associated with the number of firms in microclusters in local urban areas. Still, a dense set of informal social networks attracts creative business in core urban zones, with little influence on rural locations. Even though

¹⁹ Our results broadly hold when we used distance to the nearest higher education institution. Results available upon request.

²⁰ An example would be Bicton College in Devon, which is in a highly rural area that does not contain much business space at all within the corresponding LSOA.

the variable used in our analysis is an imperfect proxy of social capital, this result opens the avenue for policy to encourage the formation of informal networks to connect business and people to places.

When examining the relationship between agglomeration, spillovers and the number of microcluster firms in the local area, the coefficients obtained suggest a strong and positive correlation between related diversity, unrelated diversity and microclustering for urban and rural areas. For the case of related variety, which measures the distribution of employees between 5-digit industries within each 2-digit sector, regions with a high degree of related activities are more likely to have companies located as a part of a microcluster.²¹

Another important finding is that the coefficient of unrelated diversity, which captures the degree to which firms operate in different industries that share very limited similarities, is also positive and statistically significant across models for both samples. This finding, while preliminary, supports the idea that regions that host a highly diverse productive structure (including creative and non-creative industries) are also more likely to host microclusters. In other words, local interactions and spillovers outside the industry may drive agglomeration processes even in rural areas and offer regional resilience to sectoral economic shocks, unlike in single sector regions. This combination of findings supports the conceptual premise that the process of agglomeration in rural areas is not only driven by the co-agglomeration of similar industries (referred to in the literature as Marshall externalities), but also by a diverse set of unrelated industries (known as Jacobs externalities).

We also observe some differences between rural and urban areas regarding industry specialisation, measured by location quotients for creative industries businesses. For the case of rural regions, the industrial specialisation of creative firms was statistically significant and positive (as shown by the coefficient associated with the LQ of CIs in Table 6). This result could suggest that microclustering increases with a higher specialisation in the creative sector. However, this result does not hold for the case of urban areas (which is in line with some of the findings in Siepel et al., (2020), which highlighted the differences between companies within and outside microclusters in larger creative clusters). Regarding the specialisation of other activities such as manufacturing outside the creative sector, we do not observe any significant association between higher levels of (for instance) manufacturing and microclustering for rural firms. One possibility that could explain this result is that population-serving firms do not find it advantageous to locate in rural settings where the demand they can pull is too low (Goffette-Nagot and Schmitt, 1999). Another possibility is that rural creative industries are relatively less connected to industrial, that is non-creative, value chains. The number of creative microclusters in urban areas, on the other hand, is negatively associated with the specialisation of manufacturing and education activities.

When we control for the presence of agglomeration and urbanisation economies, we find that the area's population density is associated with the number of microclustered firms in both rural and urban areas (see coefficients of *ln_pop* in columns 1-3 and 5-7). The coefficient for distance to main city shows that the number of microclustered firms increases with distance to the main city. This result also holds for the case of the urban regions. Together these results suggest that microclusters might serve effectively as substitutes for the urban economies the further removed they are. When we consider unemployment and microclustering, we find a negative and statistically significant result,

²¹ This correlation holds even after including population density, which is thought to have a high correlation with these factors.

in line with previous research showing that creative industries firms are less likely to be located in more deprived places with higher rates of unemployment.

Table 6. Negative binomial regressions explaining the number of firms in microclusters (within 1km²-LSOA)

	Rural				Urban			
	(1) mc_stock	(2) mc_stock	(3) mc_stock	(4) mc_stoc k	(5) mc_stoc k	(6) mc_stock	(7) mc_stock	(8) mc_stoc k
ln_cultural_inst	0.618*** (0.0892)	0.621*** (0.0905)	0.613*** (0.0911)	0.497*** (0.0862)	1.447*** (0.0477)	1.191*** (0.0513)	1.183*** (0.0515)	0.695*** (0.0485)
ln_socialk		0.425 (0.233)	0.422 (0.233)	0.540 (0.235)		1.393*** (0.145)	1.394*** (0.145)	0.964*** (0.111)
ln_universities		3.934*** (1.061)	3.900*** (1.060)	4.258*** (1.058)		1.216** (0.427)	1.219* (0.429)	2.704*** (0.483)
ln_colleges		1.567 (0.814)	1.577 (0.817)	1.226 (0.708)		1.419*** (0.220)	1.416*** (0.220)	1.169*** (0.228)
ln_nature			0.0734 (0.117)	0.00354 (0.115)			0.208 (0.147)	0.0824 (0.128)
RD				1.020*** (0.241)				2.345*** (0.116)
UD				0.511*** (0.105)				0.927*** (0.0609)
LQ_cis				0.0845** (0.0394)				0.00722 (0.0231)
LQ_serv				-0.634 (0.334)				-0.695 (0.366)
LQ_manuf				-0.0434 (0.0725)				-0.375*** (0.0750)
LQ_know				-0.0771 (0.0481)				-0.173** (0.0534)
ln_pop	0.712*** (0.201)	0.541** (0.197)	0.528** (0.197)		0.476** (0.181)	0.479** (0.185)	0.461* (0.184)	
unemp	-0.295*** (0.0819)	-0.290*** (0.0816)	-0.292*** (0.0814)	-0.249** (0.0781)	-0.0388 (0.0461)	-0.0734 (0.0459)	- (0.0459)	-0.0450 (0.0401)
Distance2city	-0.324*** (0.0864)	-0.321*** (0.0862)	-0.318*** (0.0863)	-0.268** (0.0825)	0.313*** (0.0459)	0.321*** (0.0466)	0.323*** (0.0466)	0.356*** (0.0447)
ln_rate	-1.774 (1.003)	-1.851 (0.980)	-1.820 (0.980)	-2.729** (0.999)	-0.986 (0.541)	-0.670 (0.464)	-0.658 (0.466)	-2.116** (0.680)
ln_rate2	0.372** (0.126)	0.378** (0.123)	0.374** (0.123)	0.474*** (0.125)	0.239*** (0.0634)	0.190*** (0.0531)	0.189*** (0.0534)	0.290*** (0.0729)
N	4702	4702	4702	4702	18765	18765	18765	18765
ln_rate, ln_rate2 = 0	52.73 (0.000)	48.93 (0.000)	50.09 (0.000)	53.31 (0.000)	76.76 (0.000)	60.84 (0.000)	60.28 (0.000)	34.73 (0.000)
chi2	34566.2	43566.2	67657.4	58241.9	30752.6	38551.8	69092.9	39703.4
r2_p	0.154	0.238	0.248	0.260	0.112	0.189	0.208	0.237

Notes: Dependent variable: Number of creative firms in a cluster at the LSOA. Robust standard errors in parenthesis. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$. P-values are displayed in

parenthesis under the F-statistics. Areas with extreme values were eliminated from the analysis to minimise sensitivity to outliers.²²

4.2 Sector-specific determinants of microclustering in rural areas

As shown in Table 4, the percentage of firms in microclusters varies across subsectors. To explore this variation in more detail, we ran separate models for each of the 9 DCMS subsectors. All models are estimated using a negative binomial regression as in the previous subsection. The specification corresponds to models shown in columns (4) and (8) in Table 6, in which all key explanatory variables and controls are included. The dependent variable (*ln_stock*) corresponds to the number of firms in microclusters that belong to each of the subsectors.

As in the previous section, we also find a broadly positive and statistically significant correlation between the local area's microclusters and the number of cultural amenities, with the sole exception of IT and software subsector. This result corroborates earlier findings that clustering strongly depends on the availability of cultural institutions (Bakhshi, Lee and Mateos-Garcia, 2014). Regarding the coefficient associated with the local social capital, correlation is only significant for the music and performing arts. This finding has important implications for policy; if creative sectors in rural areas lack social networks, this opens the avenue for policies to generate and support environments for firms to connect with others through social networks, which might drive other forms of social capital and increase the resilience of clusters (Makarem, 2016; Ferrary and Granovetter, 2017)

In the regional environment, the role of universities (measured by the number of institutions in the local area) as knowledge creators is a crucial factor in microcluster formation in all sectors with the exception of 'Film, TV and Radio'. Moreover, the availability of colleges in the local area, on the other hand, associates positively with clustering in subsectors such as 'Advertising and marketing', 'IT and software', and 'Publishing'.

In the baseline regressions (Table 6), nature-based amenities (parks and gardens) did not correlate significantly with microclustering. However, when separating out the creative subsectors, this variable registers a positive correlation with microclustering for creative sectors such as 'Crafts', 'Architecture', and 'Museums and galleries'. This finding is generally consistent with the idea that local amenities are important factors in determining patterns of rural microclustering in the culture and arts industries (Bakhshi, Lee, and Mateos-Garcia, 2014).

Turning to the variables that capture agglomeration spillovers, we find some differences across sectors. First, the coefficient of related diversity is positive and significant for all sectors, but not for music and performing arts, and museums and galleries. This indicates that those sectors may be less reliant on other industries for their existence. Second, the coefficient of unrelated diversity is positive and significant across all creative sectors. This result suggests that interactions outside the industry do contribute to explaining rural creative microclustering.

²² Treatment of outliers consisted of transforming the continuous variables to $\ln(x+1)$. On the transformed variables, we next calculated means and standard deviations. Observations that were more than three standard deviations away from the mean were considered as outliers and turned into missing.

Table 7. Explaining the number of firms in microclusters by DCMS sectors: Rural LSOAs

	(1) Advertising & marketing	(2) Architecture	(3) Crafts	(4) Design	(5) Film, TV, Radio	(6) IT, Software	(7) Museums / Galleries	(8) Music & performing arts	(9) Publishing
ln_cultural_inst	0.362*** (0.101)	0.316*** (0.0941)	0.652*** (0.105)	0.266*** (0.0883)	0.318** (0.100)	0.242 (0.120)	1.217*** (0.119)	0.492*** (0.0910)	0.489*** (0.103)
ln_socialk	0.149 (0.242)	0.294 (0.201)	0.332 (0.253)	0.0374 (0.206)	0.465 (0.245)	0.397 (0.307)	0.313 (0.275)	0.647*** (0.213)	0.176 (0.270)
ln_universities	3.224 [†] (1.324)	2.523 [†] (1.056)	3.532** (1.356)	3.633*** (0.965)	2.337 (1.202)	3.539*** (0.955)	3.249** (1.129)	4.566*** (1.080)	5.499*** (1.384)
ln_colleges	2.377*** (0.539)	0.807 (0.662)	0.121 (0.680)	0.955 (0.691)	1.487 (0.782)	1.703** (0.653)	-0.336 (1.004)	0.572 (0.557)	2.870*** (0.904)
ln_nature	0.177 (0.135)	0.471*** (0.116)	0.474*** (0.145)	0.248*** (0.111)	0.326 [†] (0.129)	0.0263 (0.152)	0.439*** (0.179)	0.371** (0.122)	0.182 (0.135)
RD	1.450*** (0.277)	1.180*** (0.266)	1.453*** (0.295)	1.604*** (0.236)	0.746** (0.274)	1.825*** (0.335)	0.773 (0.411)	0.481 (0.256)	0.817 [†] (0.358)
UD	0.423** (0.143)	0.885*** (0.154)	0.726*** (0.161)	0.555*** (0.119)	0.564*** (0.146)	0.734*** (0.170)	0.581*** (0.203)	0.552*** (0.130)	0.740*** (0.178)
LQ_cis	0.0413 (0.0328)	0.0436 (0.0347)	0.0186 (0.0399)	0.0291 (0.0283)	0.0253 (0.0374)	0.147*** (0.0360)	-0.0220 (0.0445)	0.0480 (0.0358)	0.0189 (0.0366)
LQ_serv	-0.644 (0.390)	-0.845 [†] (0.404)	-1.296 [†] (0.518)	-0.479 (0.345)	-0.735 (0.397)	-1.163** (0.426)	-2.182*** (0.551)	-0.113 (0.416)	-0.831 (0.473)
LQ_manuf	-0.0712 (0.0884)	-0.0724 (0.0864)	-0.207 (0.109)	0.00902 (0.0754)	-0.148 (0.0872)	-0.0268 (0.0940)	-0.346** (0.124)	-0.102 (0.0906)	-0.146 (0.105)
LQ_know	-0.195** (0.0617)	-0.138 [†] (0.0612)	-0.0958 (0.0740)	-0.188*** (0.0523)	-0.174** (0.0603)	-0.209** (0.0662)	-0.319*** (0.0841)	0.0986 (0.0581)	-0.163 [†] (0.0691)
Unemp	-0.198** (0.0879)	-0.140 (0.0839)	-0.275** (0.0972)	-0.258*** (0.0755)	-0.128 (0.0770)	-0.313*** (0.109)	-0.117 (0.105)	-0.183*** (0.0889)	-0.0426 (0.0857)

	(1) Advertising & marketing	(2) Architecture	(3) Crafts	(4) Design	(5) Film, TV, Radio	(6) IT, Software	(7) Museums / Galleries	(8) Music & performing arts	(9) Publishing
distance2city	-0.239 ^{***} (0.0878)	-0.329 ^{***} (0.0780)	0.0736 (0.103)	-0.127 (0.0736)	-0.254 ^{***} (0.0787)	-0.290 ^{***} (0.0955)	0.186 (0.135)	-0.183 ^{**} (0.0820)	-0.0584 (0.0903)
ln_rate	-1.777 (1.172)	-3.991 ^{***} (1.173)	-2.123 (1.527)	-1.525 (1.066)	-0.784 (1.148)	-4.880 ^{***} (1.430)	-5.283 ^{**} (1.643)	0.456 (1.162)	-2.130 (1.299)
ln_rate2	0.340 [·] (0.142)	0.600 ^{***} (0.145)	0.348 (0.186)	0.284 [·] (0.133)	0.174 (0.142)	0.729 ^{***} (0.173)	0.776 ^{***} (0.204)	0.0299 (0.142)	0.361 [·] (0.160)
<i>N</i>	4702	4702	4702	4702	4702	4702	4702	4702	4702
ln_rate, ln_rate2 = 0	680.16 ^{***} (0.000)	342.01 ^{***} (0.000)	236.76 ^{***} (0.000)	212.16 ^{***} (0.000)	880.16 ^{***} (0.000)	450.01 ^{***} (0.000)	226.76 ^{***} (0.000)	227.16 ^{***} (0.000)	232.76 ^{***} (0.000)
Pseud <i>R</i> ²	0.368	0.299	0.259	0.241	0.135	0.184	0.293	0.254	0.259
Chi2	123574.5	116032.6	93115.4	119187.8	88302.9	89228.8	79759.5	97804.8	124574.9

Notes: Robust standard errors in parenthesis. TTWA fixed effects included in all models

[·] $p < 0.05$, ^{**} $p < 0.01$, ^{***} $p < 0.001$

4.3 Robustness checks

In our previous regressions, we use a finer geographical area – the LSOA – which represents a catchment area of 1,500 residents on average. However, by using this level of granularity, we could potentially ignore dynamics that extend beyond this geographical grid. To test for this granularity, we now change the unit of analysis to a higher level of geographical aggregation, corresponding to Middle Layer Super Output Areas (MSOA). MSOAs are built from groups of contiguous LSOA, capturing 7,200 inhabitants on average. Table A4 in the appendix reports the regression estimates from table 6 but now using MSOAs as the unit of analysis. All variables measure the number of X in the MSOA, where X corresponds to firms or amenities depending on the variable type. The estimates obtained broadly confirm our previous results, once accounting for a higher level of geographical aggregation. Note that the coefficients of unrelated diversity (*UD*) and the number of universities (*log_universities*) became statistically insignificant, whilst the coefficient for colleges is now statistically significant. One possible interpretation is that these factors may not influence the level of microclustering beyond a certain geographical distance.

Given that the dynamics of microclustering could extend beyond the local area, we need to control for the potential influence of neighbours on the location of creative microclusters. In other words, one could expect that geographical areas hosting microclusters could exercise influence on their neighbours (spillovers across geographical units). This type of influence generates spatial dependence across geographical units, which could cause an omitted variable bias (Paelinck, 2000). We also estimated a spatial autoregressive model (SAR) to correct this.²³ We used the same covariates as in all previous regressions, whilst the dependent variable corresponds to the log of microcluster firms in the MSOA (*ln_stock*).

Table A5 in the appendix reports the main results for both samples (rural and urban locations). Columns 1 and 5 report regression estimates for a spatial lag autoregressive model (i.e., the dependent variable, *ln_stock*, enters as an explanatory variable). We can see that the coefficient is statistically significant, confirming that the count of creative firms in microclusters behaves with a spatial structure. Models in columns 2 and 6 estimate an autoregressive model with a spatially autocorrelated error term (*e.ln_stock*). This variable is statistically significant. A model that combines a spatial and error lag model is estimated in columns 3 and 7. The final model (in columns 4 and 8) corresponds to a mixed regressive-spatial autoregressive model with spatial autocorrelation in the independent variables. All tests on the spatially autocorrelated error terms (*e.ln_stock*) are statistically significant. The variable associated with the spatially autocorrelated error term is statistically significant across these models. Considering the final model (columns 4 and 8), spatial autocorrelation in the independent variables is statistically significant only for urban areas. Overall, results from spatial models seem to confirm our general results.

²³ We use a contiguous spatial weight matrix. Before estimating models, we checked global spatial dependence by means of Geary's c and Getis & Ord's G tests. The null hypothesis of no spatial dependence was rejected (p-value=0.000).

5. Discussion and conclusions

This study presents new evidence about the extent and drivers of clustering in rural creative industry businesses. The report built on previous literature on spatial agglomeration in creative clusters and extended this work to rural settings. We identified creative microclusters at the street level by using websites of 184,791 creative industries businesses in England. Using a clustering algorithm, we identified 86 rural creative 'microclusters'. We then explored the determinants of clustering and analysed the differences between rural and urban microclusters. Our results, while exploratory, suggest that even in rural settings, creative industries are likely to cluster, with 35% of organisations in our sample of rural firms being located within the 86 clusters we identify.

In light of the importance of micro geographies for the understanding of creative people and places, our study complements previous research efforts in identifying creative microclusters in the UK by Siepel et al. (2020). They documented 709 different creative microclusters across the UK, with a third of them located outside the UK's big cities. Indeed, 90% of the rural microclusters that we identified were located in close proximity (0 to 10 Kms) to one of the 709 previously identified microclusters.²⁴ This finding suggests that rural creative industries play an important role in the shape and composition of the UK's creative microclusters.

Our primary finding suggests that the determinants of microclustering are generally consistent between rural and urban settings. In both cases, we find that microclustering is associated with heritage and culture-led facilities and a diverse set of local industries that share several similarities (related diversity). This finding is important because it suggests that factors associated with microclustering are *not* particularly different in rural settings. From this perspective our findings support the possibility for culture-led regeneration and placemaking, creating what Ray (2001) refers to as 'culture economies,' in line with efforts like the Creative Development Fund to use culture and creative industries as a basis for local regeneration. We do find some differences between rural and urban microclusters, but these appear to relate to the level of geography used in the analysis. In particular, we note the importance of universities and FE colleges in rural and urban areas for creative microclustering; this result is important in a rural context given shifts in the HE funding landscape, in which creative courses in post-1992 universities are increasingly being shuttered due to decreasing demand. One implication of this change in the offering of these degrees may be that associated creative microclustering may subsequently be endangered by these changes.

Ultimately, this research points to the existence of rural clusters at a lower geographical level while recognising their complex characteristics. In line with recent NICRE research (NICRE 2021a, 2021b) and PEC research (Siepel et al. 2020, 2021) our findings suggest that the Government's current levelling up agenda would benefit from recognising the distinctive features of location of rural creative industries outside of cities, and considering a more nuanced place-based approach (DCMS, 2018a). In particular, our research suggests that rural creative clusters have a meaningful contribution to make to the Levelling Up agenda. Efforts to support creative industries should therefore not overlook or otherwise exclude rural clusters in favour of cities; indeed, targeting supports to help microclusters and clusters wherever they are will help to unlock the potential of the creative industries across the UK. Where rural-specific interventions are designed, efforts

²⁴ We analyse the distance between microcluster centroids from the two studies. Note that our approach slightly differs from Siepel et al., (2020) as our population of firms corresponds to creative firms located in England's rural towns and villages.

that support the development of informal networks of interactions between rural people and organisations and stimulate local demand look to be one promising tool.

To conclude, our results should be interpreted with caution as we face some limitations. Firstly, although we use a novel data set, its structure is cross-sectional, giving little room to control for potential sources of endogeneity (e.g., the location patterns of creative microclusters could be explained by the innovativeness embedded in places and regions or by the geography of relative affluence). Second, our data reflects spatial distribution, but we cannot control for firm-level characteristics such as age, size and type of the organisation. These issues would deserve further research. Third, because we are capturing spatial clustering, we are in this study not able to make a statement about the existence of agglomeration economies *per se* in the rural microclusters we have seen. Fourth, our data relies on LSOA and MSOA geographical boundaries (and radii from these) so these results may reflect issues of catchment areas and granularity of data, which could plausibly be different in rural settings. This is a topic for future research through the PEC/NICRE collaboration. Finally, the relationships we have identified are based on pre-Covid data. The impact of Covid on rural microclusters is important in multiple ways – both in terms of changing spatial distributions of business activities as a result of the pandemic as well as the resilience of rural microcluster businesses.

Acknowledgements

We would like to thank the many people who have helped us to develop this research: First and foremost, we are grateful to NICRE for providing funding to develop this research. We like to thank Bruce Tether, Ben Kulka and Eliza Easton at the PEC and Ulrike Hotopp at NICRE for providing a thorough revision of a preliminary version of this report. We also like to thank the people who attended presentations of this study at the Creative Rural Livelihoods conference (Newcastle University) and at the Creative Industries mobiliser group Seminar (University of Sussex) and who provided constructive comments. We also like to thank NICRE and PEC communication teams for their support towards the publication of this report.

References

- Aarstad, J., Kvitastein, O. A., & Jakobsen, S. E. (2016). Related and unrelated variety as regional drivers of enterprise productivity and innovation: A multilevel study. *Research Policy*, 45(4), 844-856.
- Aharonson, B. S., Baum, J. A., & Feldman, M. P. (2007). Desperately seeking spillovers? Increasing returns, industrial organisation and the location of new entrants in geographic and technological space. *Industrial and corporate change*, 16(1), 89-130.
- Andres, L., & Round, J. (2015). The creative economy in a context of transition: A review of the mechanisms of micro-resilience. *Cities*, 45, 1-6.
- Arauzo-Carod, Josep-Maria, Daniel Liviano-Solis, and Miguel Manjón-Antolín (2010). Empirical studies in industrial location: An assessment of their methods and results, *Journal of Regional Science* 50(3) (2010), 685-711.
- Argent, N. (2019) Rural geography III: marketing, mobilities, measurement and metanarratives. *Progress in Human Geography*, 43(4), 758-766.
- Arzaghi, M., and Henderson, J. V. (2008). Networking off madison avenue. *The Review of Economic Studies*, 75(4), 1011- 1038.
- Bakhshi, Hasan, Neil Lee, and Juan Mateos-Garcia. *Capital of Culture?: An Econometric Analysis of the Relationship Between Arts and Cultural Clusters, Wages and the Creative Economy in English Cities*. (2014). National Endowment for Science, Technology and the Arts, 2014.
- Balfour, B., Fortunato, M-P. and Alter, A. (2018) The creative fire: an interactional framework for rural arts-based development. *Journal of Rural Studies* (63), 229-239.
- Barney, J. (1991). Firm resources and sustained competitive advantage. *Journal of Management*, 17(1), 99-120.
- Bell, D., & Jayne, M. (2010). The creative countryside: Policy and practice in the UK rural cultural economy. *Journal of Rural Studies*, 26(3), 209-218.
- Berg, S. H., & Hassink, R. (2014). Creative industries from an evolutionary perspective: A critical literature review. *Geography Compass*, 8(9), 653-664.
- Bergman, E.M., & Feser, E.J. (1999). *Industrial and Regional Clusters: Concepts and Comparative Applications*. Reprint. Edited by Scott Loveridge and Randall Jackson. WVU Research Repository, 2020.
- Bloom, M., Camerani, R., Casadei, P., Masucci, M., Siepel, J., and Velez-Ospina, J. (2020). Evolution and trends of creative cluster research: A systematic literature review and future research agenda. Creative Industries Policy and Evidence Centre. PEC. Nesta. Evidence Review: 2020/02.
- Boix, R., Hervás-Oliver, J. L., & De Miguel-Molina, B. (2015). Micro-geographies of creative industries clusters in Europe: From hot spots to assemblages. *Papers in Regional Science*, 94(4), 753-772.

- Boschma, R. A. (2005). Proximity and innovation: A critical assessment. *Regional Studies*, 39, 61–74. DOI: <https://doi.org/10.1080/0034340052000320887>
- Boschma, R., Martin, R., 2007. Editorial: Constructing an evolutionary economic geography. *Journal of Economic Geography*, 7(5), 537-548.
- Boschma, R. A., & Fritsch, M. (2009). Creative class and regional growth: Empirical evidence from seven European countries. *Economic geography*, 85(4), 391-423.
- Boschma, R. (2014). Constructing regional advantage and smart specialisation: Comparison of two European policy concepts. *Constructing regional advantage and Smart Specialisation: comparison of two European Policy Concepts*, 51-68.
- Boschma, R. A. (2016). Relatedness as driver of regional diversification: A research agenda. *Regional Studies*, DOI: [10.1080/00343404.2016.1254767](https://doi.org/10.1080/00343404.2016.1254767)
- Boschma, R. A., Balland, P.-A., & Kogler, D. F. (2015). Relatedness and technological change in cities: The rise and fall of technological knowledge in US metropolitan areas from 1981 to 2010. *Industrial and Corporate Change*, 24, 223–250. DOI: doi.org/10.1093/icc/dtu012
- Bosworth, G., Price, A., Collison, M., Fox, C. (2020). Unequal futures of rural mobility: challenges for a 'smart countryside'. *Local Economy* 35(6), 586-608.
- Campello, R. J., Moulavi, D., & Sander, J. (2013, April). Density-based clustering based on hierarchical density estimates. In *Pacific-Asia conference on knowledge discovery and data mining* (pp. 160-172). Springer, Berlin, Heidelberg.
- Capone, F. (2008). 14. Mapping and Analysing Creative Systems in Italy (1991–2001). *Creative cities, cultural clusters and local economic development*, 338.
- Combes, P. P., Duranton, G., & Gobillon, L. (2011). The identification of agglomeration economies. *Journal of economic geography*, 11(2), 253-266.
- Coll-Martínez, E., Moreno-Monroy, A. I., and Arauzo-Carod, J. M. (2019). Agglomeration of creative industries: An intra-metropolitan analysis for Barcelona. *Papers in Regional Science*, 98(1), 409-431.
- Coll-Martínez, E. (2019). Creativity and the city: testing the attenuation of agglomeration economies in Barcelona. *Journal of Cultural Economics*, 43(3), 365-395.
- Cooke, Philip N., and Luciana Lazeretti, eds. *Creative cities, cultural clusters and local economic development*. Edward Elgar Publishing, 2008.
- Cowie, P., Townsend, L., Salemin, K., 2020. Smart rural futures: Will rural areas be left behind in the 4th industrial revolution? *Journal of Rural Studies* 79, 169–176. DOI: [//doi.org/10.1016/j.jrurstud.2020.08.042](https://doi.org/10.1016/j.jrurstud.2020.08.042)
- Creative Rural Industries Consortium. (2019). The future is rural: The new creative rural economies. <http://www.ruralculture.org.uk/wp-content/uploads/The%20Future%20is%20Rural%20-%20The%20New%20Creative%20Rural%20Economies.pdf>

- Cruz, S. C. S., & Teixeira, A. A. (2021). Spatial analysis of new firm formation in creative industries before and during the world economic crisis. *The Annals of Regional Science*, 1-29.
- Sébastien Darchen (2016) "Clusters" or "communities"? Analysing the spatial agglomeration of video game companies in Australia, *Urban Geography*, 37(2), 202-222, DOI: <https://doi.org/10.1080/02723638.2015.1067981>
- DCMS. (2018a) Renaisi. Place Based Social Action: Learning Review. Department for Culture, Sports and Media. https://assets.publishing.service.gov.uk/government/uploads/system/uploads/attachment_data/file/937003/PBSA_Learning_Review_-_Full-FINAL__1__V2.pdf
- DCMS. (2018 b) Renaisi. Policy paper Creative industries: Sector Deal. A Sector Deal between government and the creative industries sector. 28 March 2018. <https://www.gov.uk/government/publications/creative-industries-sector-deal>
- Drennan, M. P., & Kelly, H. F. (2011). Measuring urban agglomeration economies with office rents. *Journal of Economic Geography*, 11(3), 481-507.
- Duranton, G., & Puga, D. (2004). Micro-foundations of urban agglomeration economies. In *Handbook of regional and urban economics* (Vol. 4, pp. 2063-2117). Elsevier.
- Escalona-Orcao, A. I., Escolano-Utrilla, S., Sáez-Pérez, L. A., & García, B. S. V. (2016). The location of creative clusters in non-metropolitan areas: A methodological proposition. *Journal of Rural Studies*, 45, 112-122.
- Ferrary, M., & Granovetter, M. (2017). Social networks and innovation. In *The Elgar companion to innovation and knowledge creation*. Edward Elgar Publishing.
- Florida, R. (2002). *The rise of the creative class* (Vol. 9). New York: Basic books.
- Florida, R., & Mellander, C. (2008). Music clusters. *A preliminary analysis*. *The Martin Prosperity Institute*, 18.
- Frenken, K., van Oort, F., & Verburg, T. (2007) Related variety, unrelated variety and regional economic growth. *Regional Studies* 41(5), 685-697
- Glaeser, E., Kerr, S., Kerr, W. (2015). Entrepreneurship and urban growth: an empirical assessment with historical mines. *Review of Economics and Statistics*, 97 (2), 498-520.
- Goffette-Nagot, F., & Schmitt, B. (1999). Agglomeration economies and spatial configurations in rural areas. *Environment and Planning A*, 31(7), 1239-1257.
- Gottlieb, P. D. (1995). Residential amenities, firm location and economic development. *Urban Studies*, 32(9), 1413-1436.
- Hanson, G. H. (2001). Scale economies and the geographic concentration of industry. *Journal of Economic Geography*, 1(3), 255-276.

- Harvey, D.C., Hawkins, H., Thomas, N.J., 2012. Thinking creative clusters beyond the city: People, places and networks. *Geoforum*, The Global Rise and Local Implications of Market-Oriented Conservation Governance 43, 529–539. DOI: [//doi.org/10.1016/j.geoforum.2011.11.010](https://doi.org/10.1016/j.geoforum.2011.11.010)
- Helfat, C. E., & Peteraf, M. A. (2003). The dynamic resource-based view: Capability lifecycles. *Strategic management journal*, 24(10), 997-1010.
- Hill, I. and Rowe, F. (2021). Rural creative industries - an untapped potential for UK economic recovery. National Innovation Centre for Rural Enterprise, May 2021. (Last accessed 29-8-21) <https://www.ncl.ac.uk/nicre/blog/blog-items/creative-industries>
- Hill, I. (2021) Spotlight on UK artisan entrepreneurs' situated collaborations: through the lens of entrepreneurial capitals and their conversion, *International Journal of Entrepreneurial Behavior & Research*, 27(1), 99-121
- Hill, I., Manning, L. and Frost, R. (2022) Rural arts entrepreneurs' placemaking - how 'entrepreneurial placemaking' explains rural creative hub development during COVID-19 lockdowns. *Local Economy*. 0(0). 1-23. 2022 Feb 11. DOI: <https://doi.org/10.1177/02690942221083838>
- HM Treasury, (2021) Build back better: Our plan for growth. (Last accessed 9.12.21) https://assets.publishing.service.gov.uk/government/uploads/system/uploads/attachment_data/file/968403/PfG_Final_Web_Accessible_Version.pdf
- Jones-Hall, J. (2021) *Rethinking Creative Clusters; Rethinking Creative Clusters for the Levelling-Up Agenda*. Available at: <https://culturalplacemaking.com/2021/02/09/rethinking-creative-clusters/Laundry>, C. (2008). *The creative city. A toolkit for urban innovators*. Taylor & Francis: 2nd edition.
- Knudsen, B., Florida, R., Stolarick, K., & Gates, G. (2008). Density and creativity in US regions. *Annals of the Association of American Geographers*, 98(2), 461-478.
- Lazzeretti, L., Boix, R., & Capone, F. (2008). Do creative industries cluster? Mapping creative local production systems in Italy and Spain. *Industry and innovation*, 15(5), 549-567.
- Lazzeretti, L., Capone, F., & Boix, R. (2012). Reasons for clustering of creative industries in Italy and Spain. *European Planning Studies*, 20(8), 1243-1262.
- Lazzeretti, F., Capone, A., Caloffi & S. R. Sedita (2019) Rethinking clusters. Towards a new research agenda for cluster research, *European Planning Studies*, 27 (10), 1879-1903, DOI: [10.1080/09654313.2019.1650899](https://doi.org/10.1080/09654313.2019.1650899)
- Lorenzen, M., & Frederiksen, L. (2008). Why do cultural industries cluster? Localisation, urbanisation, products and projects. *Creative cities, cultural clusters and local economic development*, 155-179.
- Mahon, M., McGrath, B., Laoire, L. O., & Collins, P. (2018). Artists as workers in the rural: precarious livelihoods, sustaining rural futures. *Journal of Rural Studies*, 63, 271-279.

- Makarem, N. P. (2016). Social networks and regional economic development: The Los Angeles and Bay Area metropolitan regions, 1980–2010. *Environment and Planning C: Government and Policy*, 34(1), 91-112.
- Malecki, E. J. (1993). Entrepreneurship in regional and local development. *International regional science review*, 16(1-2), 119-153.
- Mateos Garcia, J. & Bakhshi, H. (2016). *The geography of creativity in the UK*. London: Nesta.
- McGranahan, D. A., Wojan, T. R., & Lambert, D. M. (2011). The rural growth trifecta: outdoor amenities, creative class and entrepreneurial context. *Journal of Economic Geography*, 11(3), 529-557.
- de-Miguel-Molina, B., Hervás-Oliver, J. L., Boix, R., & De-Miguel-Molina, M. (2012). The importance of creative industry agglomerations in explaining the wealth of European regions. *European planning studies*, 20(8), 1263-1280.
- Merrell, I., Rowe, F. and Cowie, P. (2022) 'Honey Pot' Rural Enterprise Hubs as Micro Clusters: Exploring Their Role in Creativity-led Rural Development. *Local Economy*. DOI: [//doi.org/10.1177/02690942221085498](https://doi.org/10.1177/02690942221085498)
- Miles, A. and Ebury, J (2017) The village in the city: Participation and cultural value on the urban periphery. *Cultural Trends* 26 (1), 58-69.
- Naldi, L., Nilsson, P., Westlund, H., & Wixe, S. (2021). Amenities and new firm formation in rural areas. *Journal of Rural Studies*, 85, 32-42.
- National Audit Office (2022). Supporting local economic growth. REPORT by the Comptroller and Auditor General. February 2022. Access here: <https://www.nao.org.uk/wp-content/uploads/2021/06/Supporting-local-economic-growth.pdf>
- NICRE (2021a). What is the contribution of rural enterprise to Levelling Up, and how can this be further enabled? National Innovation Centre for Rural Enterprise. Briefing Paper No 1, March 2021. Access here: <https://www.ncl.ac.uk/mediav8/nicre/files/What%20is%20the%20contribution%20of%20rural%20enterprise%20to%20Levelling%20Up,%20and%20how%20can%20this%20be%20further%20enabled.pdf>
- NICRE (2021b). The strategic case for equitable recognition of rural economies in Levelling Up policies. National Innovation Centre for Rural Enterprise. Briefing Paper No 2, November 2021. Access here: <https://www.ncl.ac.uk/mediav8/nicre/files/NICRE%20Briefing%20Paper%20No%202%20November%202021%20The%20strategic%20case%20for%20equitable%20recognition%20of%20rural%20economies%20in%20Levelling%20Up%20policies.pdf>
- Nurse, A., & Sykes, O. (2020). Place-based vs. place blind?—Where do England's new local industrial strategies fit in the 'levelling up' agenda?. *Local Economy*, 35(4), 277-296.
- ONS (2016). 2011 Rural/urban classification. Newport: Office of National Statistics. <https://www.ons.gov.uk/methodology/geography/geographicalproducts/ruralurbanclassifications/2011ruralurbanclassification> [Accessed 30 April 2022]

- Ozusaglam, S., and Roper, S. (2021) It's not just where you are, it's where you want to go. Ambition, innovation and digital innovation in urban and rural micro-businesses. NICRE Research Report No. 2. May 2021.
- Paelinck, J. H. (2000). On aggregation in spatial econometric modelling. *Journal of Geographical Systems*, 2(2), 157-165.
- Pe'er, A., Vertinsky, I., & King, A. (2008). Who enters, where and why? The influence of capabilities and initial resource endowments on the location choices of de novo enterprises. *Strategic organisation*, 6(2), 119-149.
- Phillip, L. and Williams, F. (2019) Remote rural home-based businesses and digital inequalities: Understanding needs and expectations in a digitally underserved community. *Journal of Rural Studies* (68) 306-318.
- Power, T. M. (2005). The supply and demand for natural amenities: An overview of theory and concepts. *Amenities and rural development: Theory, methods and public policy*, 63-77.
- Pratt, A. C. (2021). Creative hubs: A critical evaluation. *City, Culture and Society*, 24, 100384.
- Ray, C. (2001) *Culture economies*. Newcastle upon Tyne, Centre for Rural Economy. (Last accessed 9-12-21) <https://www.ncl.ac.uk/media/wwwnclacuk/centreforruraleconomy/files/culture-economy.pdf>
- Ray, C. (2006) Neo-endogenous development in the EU, in *The Handbook of Rural Studies*, Sage, London, 278-292.
- Rammer, C., Kinne, J., and Blind, K. (2020). Knowledge proximity and firm innovation: A microgeographic analysis for Berlin. *Urban Studies*, 57(5), 996-1014.
- Roberts, E. and Townsend, L. (2016). The contribution of the creative economy to the resilience of rural communities: Exploring cultural and digital capital. *Sociologia Ruralis*, 56(2), 197-219.
- Rodríguez-Pose, A., & Hardy, D. (2015). Cultural diversity and entrepreneurship in England and Wales. *Environment and Planning A*, 47(2), 392-411.
- Scott, A. J. (2018). *On Hollywood*. Princeton University Press.
- Siepel, J., Camerani, R., Masucci, M., Velez-Ospina, J.A., Casadei, P & Bloom, M (2020). Creative industries Radar: Mapping the UK's creative clusters and microclusters. Creative Industries Policy and Evidence Centre.
- Siepel, J., Velez Ospina, J.A., Camerani, R., Bloom, M., Masucci, M., & Casadei, P. (2021) Creative Radar 2021: The impact of COVID-19 on the UK's creative industries. Creative Industries Policy and Evidence Centre.
- Townsend, L., Wallace, C., Fairhurst, G. and Anderson, A. (2017) Broadband and the creative industries in rural Scotland. *Journal of Rural Studies* (54) 451-458.

- UK Government. (2022). Levelling up the United Kingdom. White paper. Secretary of State for Levelling Up. February 2022. https://assets.publishing.service.gov.uk/government/uploads/system/uploads/attachment_data/file/1052706/Levelling_Up_WP_HRES.pdf
- Valero, A., & Van Reenen, J. (2019). The economic impact of universities: Evidence from across the globe. *Economics of Education Review*, 68, 53-67.
- Van Oort, F. G. (2017). *Urban growth and innovation: Spatially bounded externalities in the Netherlands*. Routledge.
- Verditch, M. (2010) Creative migration? The attraction and retention of the 'creative class' in Launceston, Tasmania. *Australian Geographer*, 41(1) 129-140.
- Wixe, S. (2018). Neighbourhood Related Diversity, Human Capital and Firm Innovation. *Papers in Regional Science* 97(2) 217-252.
- White, P. (2010) Creative industries in a rural region: *Creative West: The creative sector in the Western Region of Ireland*. *Creative Industries Journal* 3(1) 79-88.
- Wolman, H. and Hincapie, D. (2015). Clusters and cluster-based development policy. *Economic Development Quarterly*, 29 (2), 135-149.
- Woods, M., (2012) Creative ruralities. Paper presented to the 'Creativity on the Edge' Symposium, Moore Institute, National University of Ireland Galway.

Appendix

Table A1. Sensitivity analysis (rural microclusters)

Minimum size	Threshold (number of firms)				
	20	25	30	40	50
Count (number of clusters)	307	216	170	105	80
Firms in microclusters	10,166	10,100	9,411	10,803	9,634
% firms in microclusters	40%	40%	37%	42%	38%
1 Km					
Median number of neighbours	10	9	8	7	7
Average number of neighbours	14	14	14	13	14
3 Km					
Median number of neighbours	23	24	24	22	23
Average number of neighbours	26	27	28	26	28
5 Km					
Median number of neighbours	36	38	39	40	42
Average number of neighbours	42	43	44	44	46
8 Km					
Median number of neighbours	68	69	69	68	69
Average number of neighbours	77	75	78	78	77

Table A2. Variable definition

Variable	Description	Unit of observation	Period
Dependent variables			
<i>Stock</i>	Microcluster stock: Number of creative firms in microclusters.	LSOA	2019
<i>Ln_stock</i>	Log of microcluster stock	MSOA	2019
Amenities			
<i>ln_cultural_intensity</i>	Number of museums, public galleries, libraries, archives, heritage site and science centres within 1km ²	LSOA	2018
<i>log_socialk</i>	The number of organisations dedicated to exhibitions, campaigns and initiatives, festivals, cultural and scientific meetings within 1km ²	LSOA	2018
<i>ln_nature</i>	Number of gardens, environmental and ecological centres, and agricultural sites within 1km ²	LSOA	2018

Variable	Description	Unit of observation	Period
<i>log_universities</i>	The number of universities within 1km ²	LSOA	2018
<i>log_colleges</i>	The number of college institutions within 1km ²	LSOA	2018
Agglomeration, industry, and size			
<i>RD</i>	Related diversity: $-\sum_{j=1}^J E_j \ln H_j$ where $H_j = -\sum_{i=1}^I E_{ij} \ln E_{ij}$ and E_{ij} denotes the share of employees that work in each 5-digit SIC industry i , where the share is measured within each 2-digit SIC industry j .	LSOA	2018
<i>UD</i>	Unrelated diversity: $-\sum_{j=1}^J E_j \ln \ln E_j$, where E_j denotes the share of total employment in each LSOA that belongs to the same 2-digit SIC code industry j .	LSOA	2018
<i>LQ_CIs</i>	Employment-based Location quotient for Creative Industries. $LQ_{s,r} = \frac{e_{s,r}}{e_s/e}$ where $e_{s,r}$ denotes the number of employees in each LSOA r and industry s . e_r denotes all employees in the LSOA, e_s the number of employees in industries s in England, and e the total number of employees in England	LSOA	2018
<i>LQ_manuf</i>	Employment-based Location quotient for Manufacturing industries	LSOA	2018
<i>LQ_serv</i>	Employment-based Location quotient for Service industries	LSOA	2018
<i>LQ_know</i>	Employment-based Location quotient for knowledge-based industries.	LSOA	2018
Other controls			
<i>ln_pop</i>	Population density: People per kilometre square KM ²	LSOA	2018
<i>unemp</i>	Unemployment rate: Annual rate (Sep-Sep) in %	District	2018
<i>distance2city</i>	Distance to the main city in miles.	LSOA	2018
<i>ln_rate</i>	Rateable value per m ²	LSOA	2018
<i>ln_rate2</i>	Square of the rateable value per m ²	LSOA	2018
<i>Fixed effects</i>	TTWA: Travel to work areas fixed effects. 228 Dummies.	TTWA	

Notes: LSOA refers to Lower Super Output Area. MSOA refers to Middle Super Output area. Location quotients are based on employment figures from the Business register and employment survey. Sectors were classified using SIC codes as follow: Creative firms: DCMS classification (3212, 5811, 5812, 5813, 5814, 5819, 5821, 5829, 5911, 5912, 5913, 5914, 5920, 6010, 6020, 6201,6202, 7021, 7311, 7312, 7111, 7410, 7420, 7430, 8552, 9001, 9002, 9003, 9004, 9101, 9102); Manufacturing industries (10, 11, 12, 13, 14, 15, 16, 17, 18, 19, 20, 21, 22, 23, 24, 25, 26, 27, 28, 29, 30, 31, 32, 33, 36, 37, 38, 39, 41, 42, 43); Service activities (45, 46, 47, 49, 50, 51, 52, 53, 55, 56, 61, 64, 65, 66, 68, 69, 70, 7112, 7120, 7490, 75, 77, 79, 80, 81, 82, 84, 86, 87, 88, 92, 9311, 9313, 9319, 94, 95, 96, 97, 98, 99); knowledge based activities (85).

Table A3. Pairwise correlations (Full sample: rural and urban LSOAs)

Variables	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)	(13)	(14)	(15)	(16)
(1) Population den~2	1.00															
(2) Unemployment r~c	0.05***	1.00														
(3) distance2capital	-0.04***	-0.49***	1.00													
(4) Rateable value-2	0.05***	0.04***	-0.31***	1.00												
(5) Rateable value~e	0.05***	0.05***	-0.32***	0.99***	1.00											
(6) ln_cultural_insti	0.07***	-0.01*	0.06***	0.10***	0.10***	1.00										
(7) Number of uni~1K	0.05***	0.03***	-0.04***	0.05***	0.05***	0.11***	1.00									
(8) Number of coll~m	0.02***	0.02***	-0.03***	0.03***	0.03***	0.07***	0.04***	1.00								
(9) Social_capital	0.04***	0.02**	-0.01	0.10***	0.11***	0.35***	0.15***	0.07***	1.00							
(10) log parks and~s	0.04***	-0.10***	0.12***	-0.03***	-0.03***	0.15***	0.04***	0.01**	0.06***	1.00						
(11) Related variety	0.16***	-0.02**	0.01	0.17***	0.16***	0.25***	0.01**	0.08***	0.14***	0.04***	1.00					
(12) Unrelated var~y	0.18***	-0.14***	0.11***	0.01	0.01	0.18***	-0.05***	-0.02***	0.09***	0.11***	0.39***	1.00				
(13) LQ_ci	0.00	-0.04***	-0.13***	0.20***	0.21***	0.03***	0.01	-0.02***	0.04***	0.03***	-0.06***	0.13***	1.00			
(14) LQ_serv	0.04***	0.05***	-0.04***	0.22***	0.21***	0.11***	-0.06***	-0.06***	0.04***	0.00	0.16***	0.13***	-0.15***	1.00		
(15) LQ_manuf	-0.02***	-0.06***	0.14***	-0.37***	-0.37***	-0.09***	-0.05***	-0.05***	-0.08***	-0.03***	-0.04***	0.18***	-0.09***	-0.47***	1.00	
(16) LQ_know	-0.03***	0.03***	-0.04***	-0.01*	-0.02**	-0.07***	0.10***	0.12***	-0.01	-0.02**	-0.11***	-0.38***	-0.11***	-0.65***	-0.65***	1.00
																0.25

Table A4. Negative binomial Regressions explaining the number of firms in microclusters (at MSOA)

	Rural				Urban			
	(1) mc_stock	(2) mc_stock	(3) mc_stock	(4) mc_stock	(5) mc_stock	(6) mc_stock	(7) mc_stock	(8) mc_stock
ln_cultural_inst	0.832*** (0.157)	0.861*** (0.164)	0.877*** (0.165)	0.654*** (0.173)	1.186*** (0.0549)	0.917*** (0.0659)	0.911*** (0.0657)	0.649*** (0.0649)
ln_socialk		0.244 (0.386)	0.228 (0.380)	0.243 (0.379)		0.956*** (0.124)	0.949*** (0.124)	0.738*** (0.116)
ln_universities		1.706 (1.742)	1.627 (1.719)	1.833 (1.757)		0.741 (0.410)	0.723 (0.413)	1.400*** (0.402)
ln_colleges		1.928** (0.930)	2.019** (0.949)	2.132** (1.084)		0.895*** (0.217)	0.877*** (0.219)	0.686*** (0.206)
ln_nature			-0.279 (0.314)	-0.420 (0.312)			0.115 (0.167)	-0.00812 (0.173)
RD				1.942** (0.763)				1.707*** (0.266)
UD				0.382 (0.451)				1.038*** (0.169)
LQ_cis				0.424 (0.285)				0.265*** (0.0560)
ln_pop	0.847*** (0.175)	0.894*** (0.175)	0.867*** (0.174)		0.172** (0.0729)	0.135* (0.0734)	0.142* (0.0739)	
Unemp	-0.996*** (0.216)	-1.045*** (0.218)	-1.043*** (0.215)	-0.869*** (0.205)	-0.0998 (0.0688)	-0.112 (0.0709)	-0.111 (0.0707)	-0.117** (0.0585)
Distance2city	-0.217 (0.148)	-0.186 (0.150)	-0.197 (0.150)	-0.167 (0.153)	0.622*** (0.0700)	0.636*** (0.0731)	0.642*** (0.0735)	0.511*** (0.0707)
ln_rate	-6.434 (4.227)	-6.067 (4.068)	-6.174 (4.037)	-7.088 (3.964)	2.644* (1.328)	2.368 (1.397)	2.441 (1.404)	-1.584 (1.908)
ln_rate2	1.133* (0.528)	1.079* (0.509)	1.096* (0.506)	1.212* (0.489)	-0.171 (0.152)	-0.151 (0.161)	-0.160 (0.162)	0.280 (0.212)
N	1160	1160	1160	1160	5362	5362	5362	5362
ln_rate, ln_rate2 = 0	52.73***	48.93***	50.09***	53.31***	76.76***	60.84***	60.28***	34.73***
chi2	13361.6	117713	11100.7	10534.4	11761.6	13771.7	12900.7	16054.9
r2_p	0.11	0.13	0.14	0.16	0.10	0.11	0.12	0.13

Notes: Robust standard errors in parenthesis. TTWA fixed effects included in all models * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Table A5. Spatial regression model explaining the number of firms in microclusters (at MSOAs)

	Rural				Urban			
	(1) ln_stock	(2) ln_stock	(3) ln_stock	(4) ln_stock	(5) ln_stock	(6) ln_stock	(7) ln_stock	(8) ln_stock
ln_stock								
ln_cultural_inst2	0.119** (0.0563)	0.141*** (0.0540)	0.140** (0.0550)	0.115** (0.0569)	0.330*** (0.0289)	0.350*** (0.0276)	0.351*** (0.0282)	0.346*** (0.0296)
ln_socialk	0.156 (0.104)	0.139 (0.0978)	0.145 (0.100)	0.171 (0.108)	0.402*** (0.0537)	0.463*** (0.0521)	0.434*** (0.0528)	0.441*** (0.0546)
ln_universities	0.938 (0.768)	0.622 (0.725)	0.665 (0.740)	0.631 (0.725)	0.883*** (0.186)	0.815*** (0.175)	0.792*** (0.180)	0.827*** (0.176)
ln_colleges	1.102*** (0.415)	1.015*** (0.388)	1.040*** (0.398)	1.016*** (0.388)	0.593*** (0.101)	0.551*** (0.0959)	0.554*** (0.0981)	0.539*** (0.0961)
Rd	0.418* (0.240)	0.460** (0.229)	0.481** (0.234)	0.467** (0.229)	1.045*** (0.0892)	0.917*** (0.0861)	0.968*** (0.0874)	0.902*** (0.0861)
Ud	-0.00439 (0.142)	0.0272 (0.136)	0.000758 (0.138)	0.0184 (0.136)	0.111** (0.0542)	0.168*** (0.0525)	0.144*** (0.0532)	0.170*** (0.0525)
lq_cis	0.00204 (0.0630)	0.0395 (0.0617)	0.0229 (0.0623)	0.0366 (0.0618)	0.0448** (0.0212)	0.0744*** (0.0213)	0.0552*** (0.0213)	0.0796*** (0.0214)
lq_serv	-0.394 (0.244)	-0.504** (0.233)	-0.493** (0.238)	-0.499** (0.234)	0.604*** (0.127)	0.563*** (0.124)	0.570*** (0.126)	0.581*** (0.124)
lq_know	-0.0942* (0.0545)	-0.0875* (0.0515)	-0.0883* (0.0525)	-0.0836 (0.0516)	-0.0773*** (0.0197)	-0.0718*** (0.0190)	-0.0729*** (0.0193)	-0.0690*** (0.0190)
distance2capital	-0.0558* (0.0314)	-0.0389 (0.0371)	-0.0402 (0.0350)	-0.0310 (0.0377)	0.174*** (0.0166)	0.177*** (0.0217)	0.174*** (0.0191)	0.198*** (0.0230)
Unemp	0.0639* (0.0388)	0.00426 (0.0464)	0.0348 (0.0436)	0.00500 (0.0469)	-0.0501*** (0.0129)	-0.0434** (0.0175)	-0.0421*** (0.0152)	-0.0476*** (0.0176)
ln_rate	-5.438*** (1.376)	-5.446*** (1.385)	-5.609*** (1.387)	-5.540*** (1.385)	0.167 (0.443)	-0.645 (0.464)	-0.299 (0.456)	-0.799* (0.466)
ln_rate2	0.800*** (0.176)	0.800*** (0.177)	0.823*** (0.177)	0.813*** (0.177)	-0.0162 (0.0507)	0.0917* (0.0532)	0.0453 (0.0522)	0.110** (0.0535)
_cons	9.389*** (2.669)	9.644*** (2.693)	9.777*** (2.693)	9.785*** (2.692)	-1.535 (0.950)	-0.0602 (0.996)	-0.772 (0.978)	0.161 (0.999)
C1_s001								
ln_stock	0.250*		0.274*		0.252***		0.301***	

	Rural				Urban			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	ln_stock	ln_stock	ln_stock	ln_stock	ln_stock	ln_stock	ln_stock	ln_stock
ln_stock	(0.139)		(0.142)		(0.0568)		(0.0585)	
e.ln_stock		0.603*** (0.0530)	0.384*** (0.133)	0.600*** (0.0530)		0.530*** (0.0215)	0.303*** (0.0581)	0.527*** (0.0215)
ln_cultural_inst2				-0.240 (0.166)				-0.0642 (0.0920)
ln_socialk				0.193 (0.357)				-0.305* (0.169)
ln_pop				0.0487 (0.0399)				0.0287*** (0.00946)
<i>N</i>	1160	1160	1160	1160	5362	5362	5362	5362
r2_p	0.0937	0.0946	0.0888	0.0976	0.229	0.227	0.223	0.229
chi2	139.4***	129.4***	134.2***	132.1***	1751.1***	1624.0***	1686.2***	1640.5***
chi2_c	3.234***	129.7***	81.82***	131.7***	19.71***	606.7***	450.5***	618.8***

Notes: Robust standard errors in parenthesis. TTWA fixed effects included in all models * p<0.10, ** p<0.05, *** p<0.010

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