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Exploring the micro-geography of innovation in England: Population density, accessibility and innovation revisited

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ABSTRACT

Innovation is driven by knowledge; technological, commercial and strategic. Knowledge may be acquired or generated through local learning or through non-local interaction. Recent studies have emphasised the micro-geography of such interactions and related innovation outcomes in an urban context. Here, we extend this micro-geographic approach to rural areas and, we believe for the first time, examine the role of population density and accessibility in shaping innovation intensity in each of the 32,000 Lower Super Output Areas or LSOAs in England. Our analysis focuses on firms' registered intellectual property – patents, trade marks and registered designs. Our analysis suggests three key results. First, we find a positive relationship between population density and innovation intensity. For example, a 1 per cent increase in population density is associated with a 0.15-0.17 per cent increase in patent intensity. Second, we find a consistent negative relationship between journey time to the nearest town centre and innovation intensity. For instance, at variable means, a one per cent increase in journey time is associated with a fall of 0.15-0.18 per cent in patent intensity. Third, we find strong interaction effects between population density and accessibility meaning that population density or sparsity effects are amplified where journey times are greater, i.e. in more remote areas. For trade mark intensity, for example, any difference in population density has 1.5 times as large an effect on innovation intensity when journey time is 80 minutes compared to a situation when journey time is 40 minutes. Our analysis suggests the value of a micro-geographic perspective on rural innovation and emphasises the positive innovation benefits of measures to improve rural mobility and strengthen local interactions.

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Keywords: Innovation; micro-geography; England; patents; trade marks; designs.

CONTENTS

1. INTRODUCTION

Innovation is driven by knowledge; technological, commercial and strategic. Firms' and individuals' ability to access and implement relevant knowledge is shaped by their own search capabilities and their ability to access learning opportunities (Keeble and Wilkinson 1999). In any specific locality, learning is related to knowledge sharing and matching (Scott and Storper 2015) and the intensity of local interactions or 'buzz' (Storper and Venables 2004). Spatial contrasts in learning processes have typically been considered at the scale of cities or regions, but more recent studies have also emphasised the micro-geographies within which innovation takes place. Rammer, Kinne, and Blind (2020), for example, examine the knowledge environment for firms in Berlin and demonstrate that knowledge environments differ over distances as short as 50 to 250 metres. Other micro-geographic studies have focussed on the role of proximity within buildings and scientific sites on the extent of collaborative research outputs (Catalini 2018; Kabo et al. 2014). Localised learning processes, enabled by proximity, may be enhanced and reinforced by non-local knowledge sharing opportunities which may enable learning (Hjaltadottir, Makkonen, and Mitze 2020) and help avoid local lock-in (Visser and Boschma 2004) through knowledge pipelines (Trippl, Todtling, and Lengauer 2009; Aarstad, Kvitastein, and Jakobsen 2016; Esposito and Rigby 2019).

These conceptual arguments imply that levels of innovation will typically be lower in rural areas due to lower levels of local interaction, knowledge exchange and weaker endogenous and non-local learning processes (Scott and Storper 2015). The empirical evidence for the UK, however, tells a rather different story. Early evidence suggested that rural firms were actually more likely to be innovating than firms in urban areas, and also more likely to introduce new to the market innovations (Cosh and Hughes 1996). Other studies adopted a more nuanced approach to rural economies, recognising that localised disadvantages in terms of interaction and learning related to sparse populations may be reinforced where accessibility is limited and therefore access to external learning opportunities is costly (Hansen 1959;Wu et al. 2020). Based on a study of UK firms, Keeble and Tyler (1995, p. 989) for example, concluded that: 'accessible rural firms are more dynamic, innovative and technologically focused than their counterparts in either urban or remote rural locations'. This type of evidence suggests the potential for (non-linear) reinforcing effects of population density and accessibility on the development potential of remoter rural areas[1]. North and Smallbone (2000) suggest the importance of areas' sectoral mix in generating these results, but also suggest that UK firms in accessible but rural areas were more likely to have adopted new technologies than those in more remote rural locations. 'In aggregate SMEs in remote rural areas are less innovative than SMEs in accessible rural areas because firms in the more innovative sectors are under-represented' (North and Smallbone 2000, p. 155). More recent survey evidence for England also points to higher levels of innovative activity in rural than urban areas but also highlights significant differences in innovation outcomes between types of rural area (Phillipson et al. 2019).

Each of these studies of innovation in urban and rural areas in the UK has been based on business survey data. Due to limited sample sizes this often restricts the unit of analysis to be relatively large regions or categories of rural area (Phillipson et al. 2019). Here, using data on all UK firms registered intellectual property – patents, trade marks and registered designs – we are able to adopt a micro-geographic, population-wide approach to consider the individual and combined impacts of population density and accessibility on innovation in small areas (Lower Super Output Areas or LSOAs) in England. Our estimation sample includes data for around 32,000 English LSOAs with a mean population of around 1700 and mean land area of around 4 square km although both indicators vary widely between LSOAs. For each LSOA we construct indictors of patent, trade mark and design intensity which form the dependent variables for our analysis. Patents are often viewed as the first-choice innovation protection instrument, and 'protect new inventions and cover how products work, what they do, how they do it, what they are made of and how they are made' (Athreye 2019)[2]. Patents are frequently used as an indicator of innovation, particularly in knowledge intensive industries, although this approach has often been questioned (Turner and Roper, 2020). Trade marks protect brands, be it a business name, a product or a service, and have also been used as an innovation indicator (Mendonca, Pereira, and Godinho 2004). A design registration "…protects the visual appearance of a product, part of a product, or its ornamentation" (IPO 2018), providing it is new and has individual character[3]. Fewer studies have considered the role of registered designs in innovation, but

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[1] Vaessen and Keeble (1995), however, have argued that these disadvantages may be offset if firms in more marginalised areas compensate by intensifying their innovation efforts. Eder and Trippl (2019) provide recent evidence of such 'compensation' practices by firms in peripheral regions of Austria.
[2] https://www.gov.uk/government/publications/ip-basics/ip-basics
[3] Confusion sometimes arises between the protection offered by a design registration and that offered by a patent: a design registration protects the visual appearance of a product whereas a patent protects a technical product and how it functions.

recent UK evidence suggests a strong relationship between registered designs and both the propensity to innovate and the returns to innovation (Turner and Roper, 2020).

We contribute to the limited literature on the spatial distribution of innovation by addressing three main research questions. First, we consider how population density impacts on innovation outcomes in around 32,000 Lower Layer Super Output Areas (LSOAs) in England. Conceptual considerations related to buzz suggest we might anticipate a negative relationship (Storper and Venables 2004) although as indicated earlier the prior empirical evidence for the UK is less clear. Second, we consider the role of accessibility – measured by journey time to the nearest town centre - in shaping innovation outcomes in each LSOA. Here, theoretical considerations and the limited empirical evidence are more closely aligned suggesting a negative relationship (North and Smallbone 2000). Thirdly, we consider whether population density and accessibility effects exacerbate each other to create particular innovation challenges in more remote and sparsely populated LSOAs. Fourthly we contribute to the evolving literature on the micro-geography of innovation (Rammer, Kinne, and Blind 2020), including rural areas in this type of analysis for the first time. This builds on typological studies which combine population density and accessibility indicators for individual localities (Copus et al., 2007; Pizzoli and Xiaoning, 2007) but provides a more flexible and nuanced framework within which the innovation potential of individual small areas can be considered.

The argument proceeds as follows. Section 2 briefly reviews the existing literature on population density, accessibility and innovation and develops our hypotheses. Section 3 describes our data sources and empirical approach. We combine intellectual property data for 82,900 companies which held live patents, trade marks or registered designs within our study period with population density and accessibility data for each of the 32,000 Lower Layer Super Output Areas (LSOAs) in England controlling for a range of other local characteristics. Section 4 describes our main results. Section 5 summarises the key findings and considers the implications for policy and future research.

2. CONCEPTUAL DEVELOPMENT

2.1 Population density and accessibility

'Population density is a quintessentially spatial phenomenon, expressing the way that human beings spread out over, and occupy, the earth. As such it is a highly significant element in population geography' (Smailes et al. 2002, p. 386). Early discussion in the economic geography literature recognised the importance of the distribution of population in space and stressed trade-offs between economies of agglomeration, congestion, and transport costs within the framework of central place theory (Christaller 1933; Losch 1940). More recent ideas in economic geography also stress the balance of forces which may either increase (centripetal) or reduce (centrifugal) density in urban areas with implications for the agglomeration economies – congestion trade-off (Krugman, 1998).

Population density, or more accurately sparsity, has often been used to characterise and define 'rural' areas. 'Rural is often derived from population criteria (such as size or density) and rural is often seen as a residual category, i.e. non-urban' (Copus et al. 2008, p. 47). OECD (1996), for example, classified areas (local administrative units) as rural if they had a population density below 150 people per km square[4] [5]. Dijkstra and Poelman (2010) defined a new rurality typology based on population density but based on a population grid rather than local administrative units. In their analysis, urban areas (1km grid squares) are defined as meeting: (1) a population density threshold (300 inhabitants per km^2) and (2) a minimum size threshold (5000 inhabitants) applied to grouped grid cells above the density threshold. Rural grid squares are those outside these urban areas[6]. As with the OECD (2006) typology, regions are then defined as predominantly rural if more than 50 per cent of the population live in 'rural' grid squares[7]. As Dijkstra and Poelman (2008) suggest, this

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[4] Regions were then classified as 'rural' if more than 50 per cent of the population live in rural local administrative units; 'intermediate' if between 15 and 50 per cent live in rural local units; and 'urban' if less than 15 per cent live in rural local units.

[5] See (Martinovic and Ratkaj 2015) for a recent application of the OECD approach based on population density to the case of Serbia.

[6] The allocation of specific geographies to each category also depends significantly on differences in surface area of the administrative units – NUTS2 or NUTS3 (Dijkstra and Poelman, 20010).

[7] In Dijkstra and Poelman (2010), urban areas are distinguished from intermediate areas using a marginally different threshold (20 per cent of rural grid squares) to that in the original OECD classification. Dijkstra and Poelman (2010, p. 245) suggest this change is made to 'ensure that the population share in predominantly urban regions does not differ too much from the original OECD classification applied to NUTS3 regions'.

type of one-dimensional approach to categorising geographies has the advantage of simplicity but does not capture accessibility or the proximity of any area to local cities or population centres (Fertner 2012).

This is, however, reflected in the urban-rural classification standardly used in the UK which uses population density in the immediate and surrounding areas to generate a two-dimensional classification. First, census output areas which fall into settlements with populations of more than 10,000 are classed as urban. Urban output areas are then grouped into those in three settlement types: major conurbations; minor conurbations; or, city and town. Rural output areas are also grouped using population density into three settlement types: town and fringe; village; or, hamlet and isolated dwelling. A second dimension to the typology – also based on population density – relates to the sparsity of population in surrounding areas[8]. 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'.

Accessibility, as usually defined, reflects the distribution of destinations around a particular place, the ease with which those destinations can be reached by various modes, and the amount and character of the activity found there (Handy 2020). Typically, 'studies develop the hypothesis that accessibility is inversely correlated with the rurality of a place' (Caschili et al. 2015, p. 98). Handy (2020) goes on to argue for the importance of accessibility as an analytical and planning tool as it provides 'an indication of the potential of opportunities for interaction' (Hansen 1959), and the potential for individuals to benefit from the sharing, matching and learning which define the benefits of agglomeration (Scott and Storper 2015). As such accessibility measures can provide a social indicator of the 'the quality of urban living' (Wachs and Kumagai 1973). Notions of accessibility have played an important role in the planning literature offering a 'direct link between the characteristics of flows and the characteristics of places' (Papa et al. 2016, p. 58).

More recent spatial classifications have integrated accessibility indicators with measures of population density to reflect the diversity of rural areas. 'For example, areas that are considered rural in The Netherlands would not be considered as such in Poland. Unlike the Poles, comparatively few Dutch rural inhabitants work in agriculture; in addition, they also have access to a high level of services and are well connected to urban centres' (van Eupen

[8]https://assets.publishing.service.gov.uk/government/uploads/system/uploads/attachment_data/file/539241/Guide_to_applying_the_rural_urban_classification_to_data.pdf

et al. 2012, p. 473). Dijkstra & Poelman (2008), for example, in a study of remote rural regions (at NUTS3 level) extend the 1996 OECD classification to include distance to the nearest city: 'A region is labelled 'remote' if at least half of its population lives at more than 45 minutes by road from any city of at least 50,000 inhabitants' (Dijkstra & Poelman, 2008, p. 4)[9]. Another similar typology developed in the Foresight Analysis for Rural Areas of Europe (FARO-EU) project combined measures of economic density and accessibility (van Eupen et al. 2012). Economic density – a measure strongly related to population density - was defined as the income generated in each 1km grid square. This was combined with a range of accessibility measures based on drive time to cities of different sizes, although these were found to be strongly correlated. This led to a two-dimensional classification with combinations of economic density and accessibility defining three types of rural area: peri-urban, rural and deep rural.

Other studies have exploited the continuity of accessibility indicators making use of them as part of a statistical approach to regional classification. In one of earliest studies, Cloke (1977) considered nine demographic and accessibility indicators and using PCA analysis divided areas of England and Wales into four categories: extreme rural, intermediate rural, intermediate non-rural and extreme non-rural[10]. Implicit in the Cloke (1977) model is an assumption that the urban-rural continuum is one-dimensional, something that has been widely rejected[11]. The statistical basis for these finding has also been questioned with Hedlund (2016) noting that the PCA using Cloke's variable set explained only 50.8 per cent of the internal variation. Harrington and O'Donoghue (1998) estimate an updated version of the Cloke (1977) index for the 1981 and 1991 census years based on a similar set of measures and PCA analysis. They find very stable loadings on the different variables included in the analysis and conclude overall that 'a comparison of the 1981 and 1991 rurality indices identifies the largely static nature of rurality over the decade' (Harrington and O'Donoghue 1998, p. 185)[12]. More recently, Hedlund (2016) follows Cloke (1977)

[9] The (Dijkstra and Poelman 2008) typology creates five groups of NUTS3 regions: urban regions, intermediate regions close to a city, intermediate remote regions, rural regions close to a city and rural, remote regions.
[10] Cloke (1977) used: population change, household amenities, population of women of working age, commuting-out pattern, in-migration, population density, population over 65, distance from 50k plus urban node and employment in the primary sector.
[11] See also Cloke and Edwards (1986) and Harrington (1986).
[12] Perhaps more interesting is that Harrington and O'Donoghue (1998) also consider the potential for a two-dimensional index of rurality differentiating between demographic and structural dimensions long in advance of similar analysis by van Eupen et al. (2012).

using cluster analysis to combine information from a number of labour market and demographic indicators to create a typology of areas in rural Sweden[13].

2.2 Hypotheses

Collective learning provides the basis for localities' ability to generate innovation and local competitive advantage (Keeble and Wilkinson 1999). The scope for collective learning in any locality remains an active area of research with a focus on the intensity of interaction and knowledge sharing (Hummel 2020). Central to this is the notion that face-to-face contact remains critical in facilitating knowledge exchange, particularly where ideas are emergent, exploratory or tacit (Arentze, van den Berg, and Timmermans 2012; Storper and Venables 2004). Scott and Storper (2015), for example, emphasise the role of agglomeration – reflected in higher population densities – as the source of cities' key economic advantages in knowledge sharing, matching and learning: 'Sharing refers to dense local interlinkages within production systems as well as to indivisibilities that make it necessary to supply some kinds of urban services as public goods. Matching refers to the process of pairing people and jobs, a process that is greatly facilitated where large local pools of firms and workers exist. Learning refers to the dense formal and informal information flows (which tend to stimulate innovation) that are made possible by agglomeration and that in turn reinforce agglomeration' (Scott and Storper 2015, p. 5). Previous studies have also demonstrated that levels of interaction are positively related to population density, although this link is not uniform among members of a population or between locations. For example, van den Berg, Kemperman, and Timmermans (2014) using data from a large group of Dutch respondents find different patterns and locations of social interaction depending on individuals' age, gender and physical mobility. Based on his analysis of US cities, Hummel (2020, p. 42) concludes that his own findings 'support the growing consensus in the literature that urban density is important for income growth'. Cross-country evidence suggests however that population density alone is insufficient to ensure higher income levels with only a weak positive correlation between population density and GDP per capita (Gallup et al. 1999). Greyling and Rossouw (2017) also show

[13] The five cluster categories are named: Middle-class countryside within the urban shadow; Working class countryside within the urban shadow; Countryside outside the urban shadow; manufacturing periphery and resource periphery (Hedlund 2016), Table 2, p. 466.

that for South African cities higher population density is associated with lower non-economic quality of life. On balance we suggest that:

Hypothesis 1: Local interaction

Higher levels of population density will be associated with higher levels of collective learning and stronger innovation outcomes.

Accessibility reflects the opportunities for interaction and knowledge acquisition beyond the bounds of any locality as well as acting as an indicator of the quality of life (Hansen 1959; Scott and Storper 2015; Wachs and Kumagai 1973)[14]. In this sense 'accessibility can be used to provide meaningful and useful operationalisation of proximity' (Andersson and Karlsson 2004, p. 283) and individuals' access to knowledge (Massard and Mehier 2009). General evidence of the importance of spatial knowledge spillovers is widespread (e.g. Furkova 2019), with more detailed insight into the spatial distribution of knowledge spillovers available from the literature on knowledge spillovers from universities. The classic study by Anselin, Varga, and Acs (1997) suggested that firms within a 75-mile radius of universities benefit from knowledge spillovers while international evidence suggests different patterns of spatial decay. Based on their analysis of innovation in electronics firms in Northern Taiwan, for example, Lin, Feng, and Lee (2007) find no significant spillover effect on innovation for firms more than 30km away from universities. Other studies have suggested the importance of micro-geographic effects, observing knowledge spillovers which decay rapidly – over a few hundred metres – in an urban context (Rammer, Kinne, and Blind 2020). Evidence on the positive role of localised knowledge spillovers and spatial decay suggests:

Hypothesis 2: Opportunities for proximate interaction

Accessibility will be associated with higher levels of collective learning and stronger innovation outcomes.

Discussion of the potential synergies or conflicts between local interaction and external relationships have developed as part of the literature on local buzz and external knowledge

[14] Here we focus on geographical proximity but cognitive or cultural proximity may also be important in shaping the intensity and value of interaction (Boschma 2005).

pipelines (Bathelt, Malmberg, and Maskell 2004). Both, it is argued, in isolation may have both positive and negative aspects. Overly intense local interaction can lead to lock-in, while external knowledge acquisition may have a particularly high cost-benefit ratio depending on accessibility (Esposito and Rigby 2019). Perhaps surprisingly, however, few studies have directly examined the complementarity or substitutability of local and external knowledge sharing. Aarstad, Kvitastein, and Jakobsen (2016, p. 130) summarise this as follows: ‘if local buzz and global pipelines have positive performance effects, and we in addition observe a *positive* interaction effect, we can deduce that the effect of the two concepts is multiplicative … If local buzz and global pipelines have positive performance effects, but there is *no* interaction effect, we can deduce that the two concepts do not have a multiplicative effect, but instead have an additive effect. … Finally, if local buzz and global pipelines have positive performance effects, but we also observe a *negative* interaction effect, we may deduce that the two concepts merely substitute for each other’. Using data from the Norwegian Community Innovation Survey their analysis suggests that external and local interactions are substitutes for smaller and medium firms but complementary for larger companies (with more than 200 employees). Other related studies have emphasised the multiple scales over which knowledge sharing takes place and linked more diverse knowledge sources to more radical innovation (Trippl, Todtling, and Lengauer 2009). Reflecting the ambiguity of the empirical results in Aarstad, Kvitastein, and Jakobsen (2016), we hypothesise simply that:

Hypothesis 3: Reinforcing effects

H3: Population density and accessibility effects will be inter-related in terms of their influence on innovation outcomes.

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3. DATA AND METHODS

3.1 Data

Dependent variables – innovation

We measure innovation performance in each LSOA using three variables relating to patent intensity, trade mark intensity and registered design intensity. In each case, following standard OECD practice, measures are defined as the count of live patents, trade marks and registered designs per thousand members of the working age population.

Data on individual patents granted, trade marks and registered designs was provided by IPO for the 1995-2018 period. For each patent granted this data provided the patent application number, the name of the applicant, the company reference number (CRN), the date the patent was granted and the date of any renewal payments. The trade mark data details UK trade marks in force between 1995 and 2018. Each record includes the published trade mark number, company name, the CRN, the year of registration and the next renewal date and the trade mark class. The registered design data covers designs registered in the UK during the 1997 to 2018 period. Each record includes the design number, the applicant's name, the CRN, the date of registration and any renewals which have been made. For the analysis here, we derived the number of live patents, trade marks and registered designs associated with each company (CRN) for each year during the 2011-2018 period[15].

On the IPO data provided address details of companies were often incomplete and so postcodes were matched in to CRNs using Companies House data for live businesses and the batch search facility in FAME (Financial Analysis Made Easy) for those which had ceased trading and were therefore not on the live register[16]. Of the 82,989 companies originally identified as holding either live patents, trade marks and registered designs during the 2011-18 period it proved possible to identify postcodes for 81,806 (98.6 per cent). Postcodes were then matched to LSOAs using the 2019 Postcode Directory with a 100 per cent match being achieved[17]. The patent, trade mark and registered design holdings of

[15] An IP protection mechanism is assumed to exist for a particular CRN during a given year if it is available to that CRN for more than six months in that given year.
[16] See http://download.companieshouse.gov.uk/en_output.html and https://fame.bvdinfo.com.
[17] See https://geoportal.statistics.gov.uk/datasets/ons-postcode-directory-november-2019.

firms within each LSOA were then aggregated to give the total number of patents, trade marks and registered designs held by firms in each LSOA in each year. These were then divided by the working age population for each LSOA, derived from the Annual Population Survey and accessed through NOMIS[18], to give the final intensity measures for each year. In 2016, average patent intensity was 0.185 patents per 1,000 population (Table 1) although this varied widely between areas (Figure 1). Trade mark intensity was higher on average in 2016 (4.5 per 1,000 population) and this is also reflected in trade marks' wider geographical distribution (Figure 2). The lower number of registered designs (0.12 per 1000 population) is also reflected in a more uneven geographical distribution (Figure 3).

Independent variables – population density and accessibility

We focus on two key independent variables: population density and accessibility measured by journey time to the nearest town centre. Population density (persons per square km) mid-year in 2015 for each LSOA in England is taken from the ONS calculated using mid-year population estimates (Table SAPE20DT11). Mean population density in 2015 across LSOAs was 4332 persons per square km (median 3442 ppkm^2) (Table 1). Unsurprisingly population density closely reflects the urban geography of the UK (Figure 4). Journey time is measured using the average minute travel time by car to the nearest town centre for each LSOA in 2015 as calculated by the Department of Transport[19]. Car speeds are based on actual road speeds derived from SatNav data with the only limitation being that no data is provided when journey times were greater than 180 minutes. Town centres themselves were identified from the 'English Town Centres 2004' project undertaken for the Ministry of Housing, Communities and Local Government (Cheshire et al. 2017)[20]. Average journey time to the nearest town centre was 26.3 minutes in 2015 (Table 1) although this varied widely between localities (Figure 5).

[18] See https://www.nomisweb.co.uk/.
[19] See https://www.gov.uk/government/collections/journey-time-statistics.
[20] See https://data.gov.uk/dataset/ed07b21f-0a33-49e2-9578-83ccbc6a20db/english-town-centres-2004.

Control variables

The availability of control variables by LSOA is relatively limited. Here, we use three sets of control variables derived from the English Index of Multiple Deprivation (IMD) 2015 to reflect specific local disadvantages (Smith et al. 2015), variables to reflect local employment composition and a set of regional dummy variables to pick up any broader regional influences. The seven domains of the IMD 2015 for each LSOA are themselves based on a basket of indicators, largely measured in 2012-13 (Smith et al. 2015)[21]. We use five (of the seven) domain scores as control variables relating to: Education, Skills and Training; Heath deprivation and Disability; Crime; Barriers to Housing and Services; and, the Living Environment. The remaining two domains of the IMD (relating to Income and Employment) are omitted due to potential overlaps with the dependent variables. The different domains of the IMD aim to capture different aspects of local deprivation (Smith et al. 2015). The Education, Skills and Training domain reflects skills and educational attainment among the local population. The Heath deprivation and Disability domain reflects life expectancy and aspects of poor mental and physical health. Crime measures the risk of experiencing crime locally and covers violent crimes, burglary, theft and criminal damage. Barriers to Housing and Services reflect road distances to public services as well as aspects of housing availability and homelessness. Finally, the Living Environment domain reflects both housing quality and local amenity (air quality and traffic accidents). In addition to the IMD variables we include two variables to capture local employment or industrial structure: the share of employment in manufacturing and the share of employment in business services.

3.2 Empirical approach

We estimate a cross-sectoral regression in which LSOAs are the unit of analysis relating each of our three innovation indicators in 2016 and 2017 to population density and accessibility in 2015 and including control variables for 2015. If IP_i is innovation and subscript i denotes the LSOA then we estimate:

$$IP_i = \beta_o + \beta_1 PDEN_i + \beta_2 JT_i + \beta_3 PDEN_i x\ PDEN_i + \beta_4 JT_i x\ JT_i + \beta_5 PDEN_i x\ JT_i + \beta_6 CONT_i + \varepsilon_i \quad (1)$$

[21] See https://opendatacommunities.org/data/societal-wellbeing/imd/indices.

Where $PDEN_i$ is population density, JT_i is accessibility, $CONT_i$ is the set of control variables and ε_i is the error term. Models include squared terms to capture any non-linear effects and an interaction effect to capture the potential for reinforcing density-accessibility effects. Based on estimated coefficients, we compute marginal effects at variable means to give an indication of the overall effect of population density and accessibility on innovation (Hypotheses 1 and 2). The potential for reinforcing effects is captured by the interaction term β_5. Marginal effects in this model, representing elasticities at variable means, are constructed as follows:

$$\frac{\delta \log(IP)}{\delta P log(DEN)} = \beta_1 + 2\beta_3 \log(PDEN) + \beta_5 \log(JT)$$

and

$$\frac{\delta \log(IP)}{\delta \log(JT)} = \beta_2 + 2\beta_4 \log(JT) + \beta_5 \log(PDEN).$$

Due to the cross-sectional nature of the analysis we interpret regression results as suggesting association rather than causation. Equations are estimated in log-log form meaning that marginal effects can be interpreted as elasticities. In addition to the baseline models covering all LSOAs in England we run separate models for LSOAs in each English region to check the robustness of the identified effects.

4. EMPIRICAL RESULTS

Baseline models for our three measures of innovation intensity (equation 1) for LSOAs in England are reported in Table 2. We see strong and consistent sign patterns for our population density and accessibility indicators across equations and also across estimates for 2016 and 2017. Population density has an inverted-U shape relationship to innovation intensity, i.e. as density initially increases so does innovation intensity although the marginal impact of density falls as density itself increases. Estimating the marginal effects at variable means for population density suggests a positive effect for each of our innovation intensity measures although these are not significant for patents in either year (Table 1). This provides support for Hypothesis 1 – innovation intensity is greater where population density is higher implying that sparse populations are related to lower levels of innovation intensity (Keeble and Wilkinson 1999; Storper and Venables 2004; Scott and Storper, 2015). More specifically our results suggest that at variable means a 1 per cent increase in population density is associated with a 0.010-0.012 per cent increase in patent intensity, a 0.071-0.073 per cent increase in trade mark intensity and a 0.021-0.033 per cent increase in design intensity (Table 2).

Journey time has a U-shaped relationship with innovation intensity across LSOAs, i.e. as journey time increases innovation intensity falls but with declining marginal impact (Table 2). As with population density, this effect is consistent across each innovation indicator and both 2016 and 2017. Calculating the marginal effects at variable means suggests strong and negative elasticities, providing support for Hypothesis 2, i.e. as journey time increases innovation intensity falls. Here the elasticities are notably larger than those associated with population density. At variable means, a one per cent increase in journey time is associated with a fall of 0.15-0.18 per cent in patent intensity, a 0.91-0.94 per cent fall in trade mark intensity and a 0.13-0.15 per cent fall in design intensity (Table 2).

Hypothesis 3 relates to the potential interaction effect of population density and accessibility. Estimated interaction effects are positive and strongly significant across each of the baseline models (Table 2) [22]. For given journey time, the positive interaction term reinforces the positive effect of population density on innovation intensity. The multiplicative nature of the interaction term means that this population density effect is stronger where journey time is greater, i.e. in more remote rural areas. Conversely, for a given population density, the positive interaction effect offsets the negative effect of longer journey times. The multiplicative nature of the interaction term means that this offsetting effect is weaker in localities where population density is lower.

Another way of looking at these population density elasticities is to plot elasticities across different journey times. This is done in Figures 6a, 6c, and 6e for the different innovation intensity measures with solid lines representing the elasticities and broken lines the 95 per cent confidence intervals around these estimates. Reflecting the pattern of significance of the marginal effects at variable means reported in Table 2, population density elasticities are significant for designs for all levels of journey time (Figure 6e). At low journey times, population density elasticities for patent and trade mark intensity are insignificant but become significant at longer journey times (Figures 6a and 6c). The implication is that innovation intensity is more sensitive to variations in population density when journey times

[22] These interaction effects are included in the calculation of the marginal effects of population density and journey time in Table 1.

are greater, i.e. in remoter areas. For trade mark intensity, for example, any difference in population density will have around 1.5 times as big an effect on innovation intensity when journey time is 80 minutes compared to a situation when journey time is 40 minutes (Figure 6c). Sparse populations in more remote areas therefore have a larger negative effect on local innovation intensity than they would have in areas closer to urban centres. Journey time elasticities vary relatively little as population density changes, however, a pattern which is observed both across the range of population densities (Figures 6b, 6d and 6f) and also in more sparsely populated areas (Figure 7).

Control variables vary in significance and sign but where they prove significant signs are largely what might be expected. The incidence of crime in a locality has a negative association with innovation intensity while housing and environmental quality have positive innovation links. Regional dummies are also significant in a number of cases with coefficients reflecting levels of innovation intensity relative to the base category which is the Eastern region. Positive, and generally significant, regional dummies are observed for London and the South East with negative coefficients for all other regions. This is consistent with other evidence which suggests higher levels of innovative activity in the South East of England with lower levels in more Northern and Western regions (Roper, Love, and Bonner 2015). The significance of the regional dummies in these baseline models suggests the value of considering the consistency of the population density and accessibility elasticities across regions.

Regional models for patent intensity, trade mark intensity and design intensity are given in Tables 3, 4 and 5. In each case models follow the same structure as the baseline models in Table 2 with marginal values for the elasticities related to population density and accessibility calculated at regional variable means given at the bottom of each table. Across almost all regions we see a very similar pattern of population density, accessibility and interaction effects to those in the national models (Tables 3, 4 and 5). The North West is a notable exception where population density and accessibility have a significant negative interaction effect. For given journey time, this negative interaction term reduces the positive influence of population density on innovation intensity, an effect which is larger where journey time is greater, i.e. in less accessible areas. The implication is that the innovation advantages of population density are not as great in the North West as in other regions with particular impacts in less accessible areas.

In terms of patent intensity in 2017, the marginal effects of population density are variable and insignificant across the majority of regions (Table 3). This reflects the weakly positive national elasticity (Table 2). London is an outlier in the population density – patent intensity linkage with population density having a strong negative elasticity. The implication is that within the London region, patent intensity is linked negatively to population density contrary to the positive relationship observed nationally. Reflecting the national pattern (Table 2), accessibility elasticities are negative and significant across almost all regions, with notably stronger negative effects in the West Midlands and South West (Table 3). An essentially similar regional pattern is observed for trade mark intensity in 2017, with London again an outlier in terms of the population density elasticity for trade marks (Table 4). Regional elasticities for design intensity again largely reflect the national pattern both for population density and accessibility (Table 5). In summary, our regional analysis largely confirms the national results for each of our main hypotheses. Population density elasticities in London for patent and trade mark intensity are unsurprising exceptions.

5. DISCUSSION AND CONCLUSIONS

We provide the first analysis of the micro-geography of innovation across England using new local area (LSAO) statistics for patent, trade mark and design intensity. Our analysis extends previous micro-geographic analyses of innovation in urban environments (Ramer et al. 2020). Our analysis suggests three key results. First, we find an inverted-U shape relationship between population density and innovation intensity for English LSOAs. As density increases so does innovation intensity until beyond a certain point the innovation benefits of population density start to decrease. This finding is consistent with theoretical perspectives which suggest that the extent of interaction in a locality or 'buzz' (Storper and Venables 2004) – itself related non-linearly to population density – is positively related to innovation intensity (Lawson and Lorenz 1999; Scott and Storper 2015). Second, and again supporting theoretical arguments relative to the value of accessibility in enabling interaction beyond the bounds of any locality (Hansen 1959; Scott and Storper 2015; Wachs and Kumagai 1973), we find a consistent negative relationship between journey time to the nearest town centre and innovation intensity. Moreover, the sensitivity of innovation intensity to marginal changes in accessibility are notably larger than those associated with population density. At variable means, a one per cent increase in journey time is associated with a fall of 0.15-0.18 per cent in patent intensity, a 0.91-0.94 per cent fall in trade mark intensity and a 0.13-0.15 per cent fall in design intensity.

Third, we find strong interaction effects between population density and accessibility. This suggests that the effect of a marginal change in population density on innovation intensity depends strongly on the accessibility of any locality and vice versa. Population density or sparsity effects are amplified where journey time is greater, i.e. in more remote areas. Conversely, for a given population density, the positive interaction effect offsets the negative effect of longer journey times, an effect which is stronger where population density is high. These effects both emphasise the compounding impact of accessibility and sparsity of population on innovation intensity in more remote rural areas (Keeble and Tyler 1995; North and Smallbone 2000; Phillipson et al. 2019). For trade mark intensity, for example, any difference in population density will have 1.5 times as large an effect on innovation intensity when journey time is 80 minutes compared to a situation when journey time is 40 minutes.

Previous analyses have suggested the diversity of local innovation performance across Local Enterprise Partnership (LEP) areas in England (Roper, Love and Bonner 2015). Our results here emphasise the micro-geographic impacts of population density and accessiblity as partial explanatory factors for innovation intensity across England and the compounding effects of each variable in sparsely populated and less accessible localities. From a policy standpoint, measures to change population density in specific localities are only feasible in the medium to long-term. Measures to promote accessibility and the associated knowledge sharing and innovation through reduced journey times are more fesible in the short- to medium-term and may yield significant social benefits in terms of innovation (Chatman and Noland 2011). Innovation in compact cities, for example, may benefit from the advantages of agglomeration while minimising the disadvantages associated with inaccessability (Hamidi, Zandiatashbar, and Bonakdar 2019). For more rural areas, particularly remote rural areas, our results suggest the importance of positive attempts to increase local interactions and knowledge sharing as well as strengthening access to more distant knowledge sharing opportunities. For example, while the innovation benefits of improved transport systems have long been emphasised (e.g Mahroum et al. 2007) our evidence suggests that significant accessibility gaps remain even within England and that these act to reducing innovation intensity, particularly in remote rural areas where population density is lowest. Typically, debates around rural mobility focus on social rather than economic issues. Our evidence also suggests a strong and consistent link with economic outcomes. Promoting local knowledge sharing through innovation hubs or co-working spaces may also provide the opportunity for increased local knowledge sharing and innovation. Gandini and Cossu (2019), for example, in their case study of RuralHub a co-working space near Salerno in Italy comment that ‘it fosters the learning and sharing of innovative practices. It is at once a co-living and coworking space, a research lab for social innovation and Do It Yourself (DIY) practices, a place to experiment with communitarian relations, both formally and informally, and an environment whereby participants can develop projects that involve local rural communities’ (Gandini and Cossu 2019, p. 14).

Our analysis is subject to a number of limitations. First, our data is essentially cross-sectional and so at the moment we are observing correlations rather than causation. It may be possible in the future to develop a more longitudinal perspective but the slow evolution of our two key explanatory variables for any locality creates significant challenges in establishing causality. Second, our analysis focuses on firms’ holdings of intellectual property as an innovation indictor. This provides the key to our micro-geographic approach but provides only a partial view of firms’ innovation activity. It tells us nothing, for example, about the economic value of firms’ innovation activity or their innovation returns. Thirdly, our focus is on intellectual property held only by firms. Other organisations such as public sector bodies, universities, colleges may also hold intellectual property and for the moment these are excluded from our analysis. Future work could usefully include these other innovation eco-system actors both as innovators in their own right but also as potential contributors to the innovation outcomes of co-located firms (Rammer et al. 2020).

Table 1: Descriptive statistics by LSOAs in England

	Obs	Mean	Std. Dev	Min.	Max.
Patents (per 000) 2016	34,406	0.2	0.9	0.0	10.0
Trade marks (per 000) 2016	34,741	4.5	21.3	0.0	728.7
Registered designs (per 000) 2016	34,415	0.1	0.6	0.0	7.0
Patents (per 000) 2017	34,406	0.2	0.8	0.0	16.6
Trade marks (per 000) 2017	34,741	4.3	19.8	0.0	748.9
Registered designs (per 000) 2017	34,328	0.1	0.6	0.0	7.0
Population density (ppKm2)	34,406	4332.3	4452.0	3.0	91775.0
Journey time (minutes)	32,404	26.3	15.2	5.8	124.9
Control variables	32,510	21.7	18.5	0.0	99.5
IMD Education domain	32,510	0.0	0.9	-3.3	3.5
IMD Health domain	32,510	0.0	0.8	-3.2	3.3
IMD Crime domain	32,510	21.7	10.6	0.4	72.6
IMD Housing domain	32,510	21.7	15.9	0.2	92.9
IMD Environment domain	34,331	5.9	11.8	0.0	100.0
Manufacturing share of emp.	34,331	20.8	17.7	0.0	100.0
Business services share of emp.	34,406	0.2	0.9	0.0	10.0

Note: We exclude around 1 per cent of LSOA areas with particularly high levels of IP ownership. For independent and control variables we exclude around 1 per cent of observations where patent intensity was particularly high to match the estimation sample in the patent intensity models. Variable definitions and sources in Annex 1.

Table 2: Innovation by LSOA in England: 2016 and 2017

	2016			2017		
	Patents	Trade mark	Designs	Patents	Trade mark	Designs
	b/se	b/se	b/se	b/se	b/se	b/se
Log (Pop. Density)	0.073***	0.420***	0.072***	0.064***	0.416***	0.102***
	(0.018)	(0.054)	(0.015)	(0.017)	(0.054)	(0.018)
Log (Pop. Density)^2	-0.012***	-0.070***	-0.009***	-0.011***	-0.068***	-0.012***
	(0.001)	(0.003)	(0.001)	(0.001)	(0.003)	(0.001)
Log (Journey time)	-0.308***	-1.578***	-0.229***	-0.259***	-1.515***	-0.249***
	(0.050)	(0.149)	(0.041)	(0.047)	(0.147)	(0.050)
Log (Journey time)^2	0.017***	0.082***	0.019***	0.014**	0.077***	0.020***
	(0.006)	(0.017)	(0.005)	(0.005)	(0.017)	(0.006)
Log (Pop. Density) x Log (Journey time)	0.021***	0.111***	0.011***	0.019***	0.108***	0.012***
	(0.003)	(0.009)	(0.002)	(0.003)	(0.009)	(0.003)
IMD Education domain	0.000	-0.004***	-0.000	0.000	-0.004***	-0.000*
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
IMD Health domain	0.007*	-0.008	0.004	0.007**	-0.007	0.008**
	(0.004)	(0.011)	(0.003)	(0.004)	(0.011)	(0.004)
IMD Crime domain	-0.014***	-0.036***	-0.011***	-0.012***	-0.036***	-0.013***
	(0.003)	(0.010)	(0.003)	(0.003)	(0.010)	(0.003)
IMD Housing domain	0.000*	0.004***	0.001***	0.000	0.004***	0.001***
	(0.000)	(0.001)	(0.000)	(0.000)	(0.001)	(0.000)
IMD Environment domain	0.002***	0.019***	0.002***	0.002***	0.018***	0.003***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Manufacturing share of emp.	0.005***	0.020***	0.002***	0.004***	0.019***	0.003***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Business services share of emp.	0.002***	0.012***	0.001***	0.002***	0.012***	0.001***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
East Midlands	-0.036***	-0.112***	-0.006	-0.036***	-0.107***	-0.015*
	(0.008)	(0.024)	(0.007)	(0.008)	(0.024)	(0.008)
London	0.003	0.299***	0.028***	0.003	0.299***	0.036***
	(0.009)	(0.027)	(0.007)	(0.009)	(0.027)	(0.009)
North East	-0.049***	-0.173***	-0.010	-0.046***	-0.168***	-0.018*
	(0.010)	(0.031)	(0.008)	(0.010)	(0.030)	(0.010)
North West	-0.051***	-0.154***	-0.016**	-0.047***	-0.148***	-0.021***
	(0.008)	(0.024)	(0.007)	(0.008)	(0.024)	(0.008)
South East	-0.000	0.124***	0.016***	-0.000	0.125***	0.019***
	(0.007)	(0.021)	(0.006)	(0.006)	(0.020)	(0.007)
South West	-0.019**	-0.066***	0.003	-0.018**	-0.061***	0.001
	(0.008)	(0.023)	(0.006)	(0.007)	(0.023)	(0.008)
West Midlands	-0.033***	-0.199***	-0.010	-0.028***	-0.188***	-0.016**
	(0.008)	(0.023)	(0.006)	(0.007)	(0.023)	(0.008)
Yorks and Humber	-0.043***	-0.213***	-0.008	-0.040***	-0.204***	-0.017**
	(0.008)	(0.024)	(0.006)	(0.007)	(0.023)	(0.008)
Constant term	0.472***	2.502***	0.235**	0.404***	2.371***	0.188
	(0.131)	(0.393)	(0.107)	(0.124)	(0.388)	(0.133)
Number of observations	32337.000	32658.000	32342.000	32337.000	32658.000	32342.000
BIC	16363.863	88862.396	3596.768	12711.205	87964.707	17404.602
Marginal effects						
Population density	0.012	0.071***	0.021***	0.010	0.073***	0.033***
se	(0.009)	(0.028)	(0.008)	(0.009)	(0.0277)	(0.010)
Journey time	-0.182***	-0.941***	-0.134***	-0.153***	-0.905***	-0.148***
se	(0.027)	(0.082)	(0.022)	(0.026)	(0.081)	(0.028)

Notes: Dependent variable is log patent intensity, log trade mark intensity or log design intensity. Marginal effects are calculated at the means of population density and journey time. * p<0.10, ** p<0.05, *** p<0.01.

Table 3: Patent intensity by LSOA: Regional models 2017

	East	East Midlands	London	North East	North West	South East	South West	West Midlands	Yorks and Humber
Log (Pop. Density)	0.145**	0.074	-0.278***	0.031	0.108**	0.120**	-0.029	0.091	0.096
	(0.064)	(0.067)	(0.100)	(0.073)	(0.047)	(0.050)	(0.053)	(0.072)	(0.065)
Log (Pop. Density)^2	-0.013***	-0.014***	0.002	-0.009***	-0.011***	-0.015***	-0.009***	-0.018***	-0.012***
	(0.003)	(0.003)	(0.004)	(0.003)	(0.002)	(0.003)	(0.003)	(0.003)	(0.003)
Log (Journey time)	0.044	-0.238	-0.992***	-0.195	-0.176*	-0.253*	-0.616***	-0.631***	-0.393**
	(0.186)	(0.236)	(0.368)	(0.183)	(0.103)	(0.137)	(0.132)	(0.203)	(0.167)
Log (Journey time)^2	-0.014	-0.002	0.076**	0.001	0.019*	0.016	0.045***	0.055**	0.042**
	(0.022)	(0.029)	(0.038)	(0.020)	(0.011)	(0.016)	(0.015)	(0.024)	(0.020)
Log (Pop. Density) x Log (Journey time)	0.006	0.030***	0.048**	0.023**	0.004	0.016**	0.034***	0.037***	0.012
	(0.010)	(0.012)	(0.020)	(0.012)	(0.007)	(0.008)	(0.007)	(0.012)	(0.011)
IMD Education domain	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
	(0.001)	(0.000)	(0.000)	(0.001)	(0.000)	(0.000)	(0.001)	(0.000)	(0.000)
IMD Health domain	-0.004	0.013	0.014*	0.02	0.004	-0.001	0.008	0.028*	0.022*
	(0.012)	(0.013)	(0.007)	(0.015)	(0.009)	(0.010)	(0.013)	(0.015)	(0.013)
IMD Crime domain	0.019*	-0.020*	-0.049***	-0.008	-0.014*	-0.006	-0.008	-0.01	-0.027**
	(0.010)	(0.010)	(0.008)	(0.010)	(0.008)	(0.009)	(0.011)	(0.011)	(0.010)
IMD Housing domain	0.000	0.001	0.000	0.001*	0.001	-0.001	0.000	0.001	0.001
	(0.001)	(0.001)	(0.000)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
IMD Environment domain	0.001**	0.003***	0.003***	0.003***	0.002***	0.003***	0.001***	0.002***	0.002***
	(0.001)	(0.001)	(0.000)	(0.001)	(0.000)	(0.000)	(0.001)	(0.000)	(0.000)
Manufacturing share of emp.	0.007***	0.004***	0.004***	0.004***	0.003***	0.006***	0.004***	0.005***	0.004***
	(0.001)	(0.000)	(0.001)	(0.000)	(0.000)	(0.001)	(0.000)	(0.000)	(0.000)
Business services share of emp.	0.002***	0.002***	0.001***	0.001***	0.002***	0.002***	0.002***	0.002***	0.002***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Constant term	-0.456	0.276	3.266***	0.265	0.037	0.183	1.395***	0.925*	0.477
	(0.463)	(0.557)	(0.963)	(0.507)	(0.304)	(0.352	(0.372)	(0.508)	(0.444)
Number of observations	3561	2743	4798	1642	4462	5188	3224	3435	3284
BIC	2262.868	1016.852	89.786	-293.949	813.534	3193.348	1729.994	1873.21	1546.367
Marginal effects at variable means									
Population density	0.062*	0.017	-0.184***	0.001	0.036	0.040	-0.037	0.008	0.024
	(0.033)	(0.035)	(0.055)	(0.038)	(0.024)	(0.026)	(0.027)	(0.037)	(0.034)
Journey time	0.025	-0.139	-0.567***	-0.109	-0.110*	-0.149*	-0.355***	-0.354***	-0.242**
	(0.102)	(0.130)	(0.202)	(0.101)	(0.058)	(0.075)	(0.072)	(0.113)	(0.095)

Notes: Dependent variable is log patent intensity. Marginal effects are calculated at variable means. * p<0.10, ** p<0.05, *** p<0.01.

Table 4: Trade mark intensity by LSOA: Regional models 2017

	East	East Midlands	London	North East	North West	South East	South West	West Midlands	Yorks and Humber
	b/se	b/se	b/se	b/se	b/se	b/se	b/se	b/se	b/se
Log (Pop. Density)	0.307*	0.291	0.447	-0.431*	1.072***	0.328**	0.249	0.540***	0.185
	(0.183)	(0.213)	(0.382)	(0.230)	(0.162)	(0.150)	(0.153)	(0.198)	(0.188)
Log (Pop. Density)^2	-0.062***	-0.068***	-0.075***	-0.039***	-0.091***	-0.065***	-0.059***	-0.099***	-0.060***
	(0.009)	(0.010)	(0.014)	(0.010)	(0.008)	(0.008)	(0.008)	(0.010)	(0.009)
Log (Journey time)	-1.793***	-2.494***	-3.695***	-4.705***	-0.413	-1.321***	-1.732***	-3.764***	-3.083***
	(0.526)	(0.758)	(1.371)	(0.577)	(0.357)	(0.406)	(0.381)	(0.559)	(0.483)
Log (Journey time)^2	0.110*	0.199**	0.340**	0.433***	0.036	0.048	0.110***	0.371***	0.288***
	(0.064)	(0.092)	(0.141)	(0.062)	(0.038)	(0.049)	(0.042)	(0.067)	(0.057)
Log (Pop. Density) x Log (Journey time)	0.128***	0.149***	0.109	0.254***	-0.006	0.115***	0.110***	0.183***	0.143***
	(0.027)	(0.037)	(0.075)	(0.037)	(0.024)	(0.024)	(0.021)	(0.032)	(0.030)
IMD Education domain	-0.009***	-0.001	-0.010***	-0.004**	-0.000	-0.006***	-0.007***	-0.003**	-0.003**
	(0.001)	(0.002)	(0.002)	(0.002)	(0.001)	(0.001)	(0.002)	(0.001)	(0.001)
IMD Health domain	0.037	-0.033	-0.001	0.170***	-0.022	-0.025	0.031	0.102**	0.085**
	(0.034)	(0.040)	(0.028)	(0.048)	(0.032)	(0.029)	(0.039)	(0.040)	(0.037)
IMD Crime domain	0.078***	0.003	-0.389***	-0.126***	-0.047*	0.029	0.153***	-0.047	-0.138***
	(0.029)	(0.034)	(0.030)	(0.032)	(0.027)	(0.026)	(0.031)	(0.030)	(0.030)
IMD Housing domain	0.003*	0.009***	0.005**	0.003	0.010***	-0.000	0.002	0.008***	0.008***
	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)
IMD Environment domain	0.012***	0.017***	0.037***	0.024***	0.018***	0.018***	0.008***	0.014***	0.017***
	(0.002)	(0.002)	(0.001)	(0.003)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
Manufacturing share of emp.	0.026***	0.018***	0.023***	0.011***	0.015***	0.028***	0.019***	0.017***	0.020***
	(0.002)	(0.001)	(0.002)	(0.001)	(0.001)	(0.002)	(0.001)	(0.001)	(0.001)
Business services share of emp.	0.014***	0.010***	0.007***	0.005***	0.013***	0.013***	0.012***	0.012***	0.011***
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
Constant term	3.117**	3.989**	7.119**	9.882***	-1.932*	2.530**	3.706***	5.416***	5.319***
	(1.314)	(1.784)	(3.622)	(1.603)	(1.050)	(1.043)	(1.072)	(1.401)	(1.283)
Number of observations	3612.000	2767.000	4826.000	1650.000	4488.000	5282.000	3259.000	3470.000	3304.000
BIC	9912.839	7506.028	13059.850	3519.529	12007.516	14942.598	8708.653	9003.956	8586.082
Marginal effects at variable means									
Population density	0.052	0.026	0.012	-0.371***	0.413***	0.033	0.009	0.071	-0.049
	(0.095)	(0.111)	(0.209)	(0.121)	(0.084)	(0.077)	(0.078)	(0.103)	(0.099)
Journey time	-1.037***	-1.412***	-2.223***	-2.664***	-0.336*	-0.774***	-1.007***	-2.142***	-1.820***
	(0.288)	(0.417)	(0.753)	(0.320)	(0.201)	(0.223)	(0.207)	(0.310)	(0.273)

Notes: Dependent variable is log trade mark intensity. Marginal effects are calculated at variable means. * p<0.10, ** p<0.05, *** p<0.01.

Table 5: Design intensity by LSOA: Regional models 2017

	East	East Midlands	London	North East	North West	South East	South West	West Midlands	Yorks and Humber
	b/se	b/se	b/se	b/se	b/se	b/se	b/se	b/se	b/se
Log (Pop. Density)	-0.079	0.092	-0.151	0.007	0.299***	0.023	0.127**	0.149**	0.096
	(0.060)	(0.064)	(0.138)	(0.071)	(0.054)	(0.052)	(0.056)	(0.074)	(0.068)
Log (Pop. Density)^2	-0.002	-0.012***	-0.007	-0.006**	-0.017***	-0.009***	-0.014***	-0.016***	-0.015***
	(0.003)	(0.003)	(0.005)	(0.003)	(0.003)	(0.003)	(0.003)	(0.004)	(0.003)
Log (Journey time)	-0.409**	-0.331	-1.122**	-0.419**	0.013	-0.371***	-0.306**	-0.254	-0.386**
	(0.174)	(0.228)	(0.498)	(0.179)	(0.118)	(0.141)	(0.141)	(0.210)	(0.175)
Log (Journey time)^2	0.025	0.028	0.081	0.039**	0.021*	0.025	0.028*	0.026	0.023
	(0.021)	(0.028)	(0.051)	(0.019)	(0.012)	(0.017)	(0.016)	(0.025)	(0.021)
Log (Pop. Density) x Log (Journey time)	0.032***	0.016	0.055**	0.021*	-0.023***	0.023***	0.013*	0.012	0.026**
	(0.009)	(0.011)	(0.027)	(0.012)	(0.008)	(0.008)	(0.008)	(0.012)	(0.011)
IMD Education domain	-0.001***	0.001	-0.001	0.000	-0.001	0.000	0.000	-0.001	0.001*
	(0.000)	(0.000)	(0.001)	(0.000)	(0.000)	(0.000)	(0.001)	(0.000)	(0.000)
IMD Health domain	0.028**	-0.006	-0.004	0.028*	0.017*	0.015	0.006	0.023	-0.004
	(0.011)	(0.012)	(0.010)	(0.015)	(0.011)	(0.010)	(0.014)	(0.015)	(0.014)
IMD Crime domain	0.007	-0.032***	-0.039***	-0.014	-0.017*	-0.014	0.001	0.007	-0.036***
	(0.010)	(0.010)	(0.011)	(0.010)	(0.009)	(0.009)	(0.011)	(0.011)	(0.011)
IMD Housing domain	0.000	0.002***	0.001*	0.001	0.002***	-0.001	0.003***	0.001	0.002***
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
IMD Environment domain	0.001	0.003***	0.005***	0.003***	0.003***	0.002***	0.002***	0.002***	0.003***
	(0.001)	(0.001)	(0.000)	(0.001)	(0.000)	(0.000)	(0.001)	(0.000)	(0.000)
Manufacturing share of emp.	0.004***	0.001***	0.002**	0.002***	0.002***	0.004***	0.002***	0.003***	0.003***
	(0.001)	(0.000)	(0.001)	(0.000)	(0.000)	(0.001)	(0.001)	(0.000)	(0.000)
Business services share of emp.	0.002***	0.001***	0.001***	0.000	0.002***	0.001***	0.002***	0.001***	0.001***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Constant term	1.052**	0.313	2.994**	0.704	-1.031***	0.784**	0.149	0.042	0.428
	(0.433)	(0.537)	(1.313)	(0.497)	(0.347)	(0.362)	(0.396)	(0.525)	(0.464)
Number of observations	3574	2738	4779	1643	4444	5226	3229	3431	3278
BIC	1804.239	834.319	3169.393	-345.971	2005.85	3640.955	2173.125	2123.542	1821.93
Marginal effects at variable means									
Population density	-0.051	0.030	-0.120	-0.009	0.144	-0.011	0.054	0.053	0.022
	(0.031)*	(0.034)	(0.075)	(0.038)	(0.028)***	(0.027)	(0.029)*	(0.039)	(0.036)
Journey time	-0.227	-0.195	-0.655	-0.241	-0.013	-0.215	-0.170	-0.146	-0.235
	(0.095)**	(0.126)	(0.274)**	(0.099)**	(0.066)	(0.077)***	(0.077)**	(0.116)	(0.099)**

Notes: Dependent variable is log design intensity. Marginal effects are calculated at variable means. * p<0.10, ** p<0.05, *** p<0.01.

Figure 1: Patent intensity by LSOA - 2016

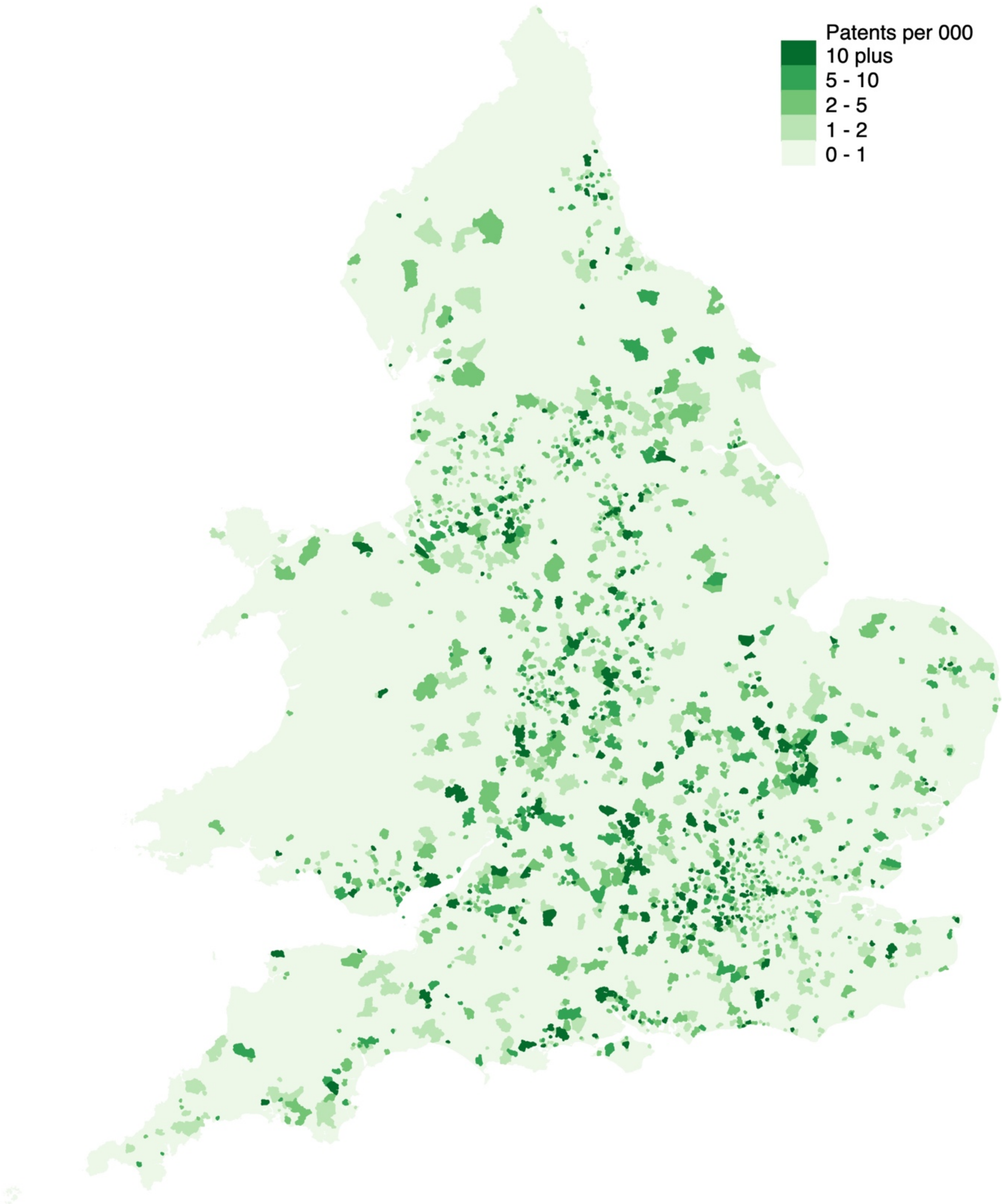


Figure 2: Trade mark intensity by LSOA - 2016

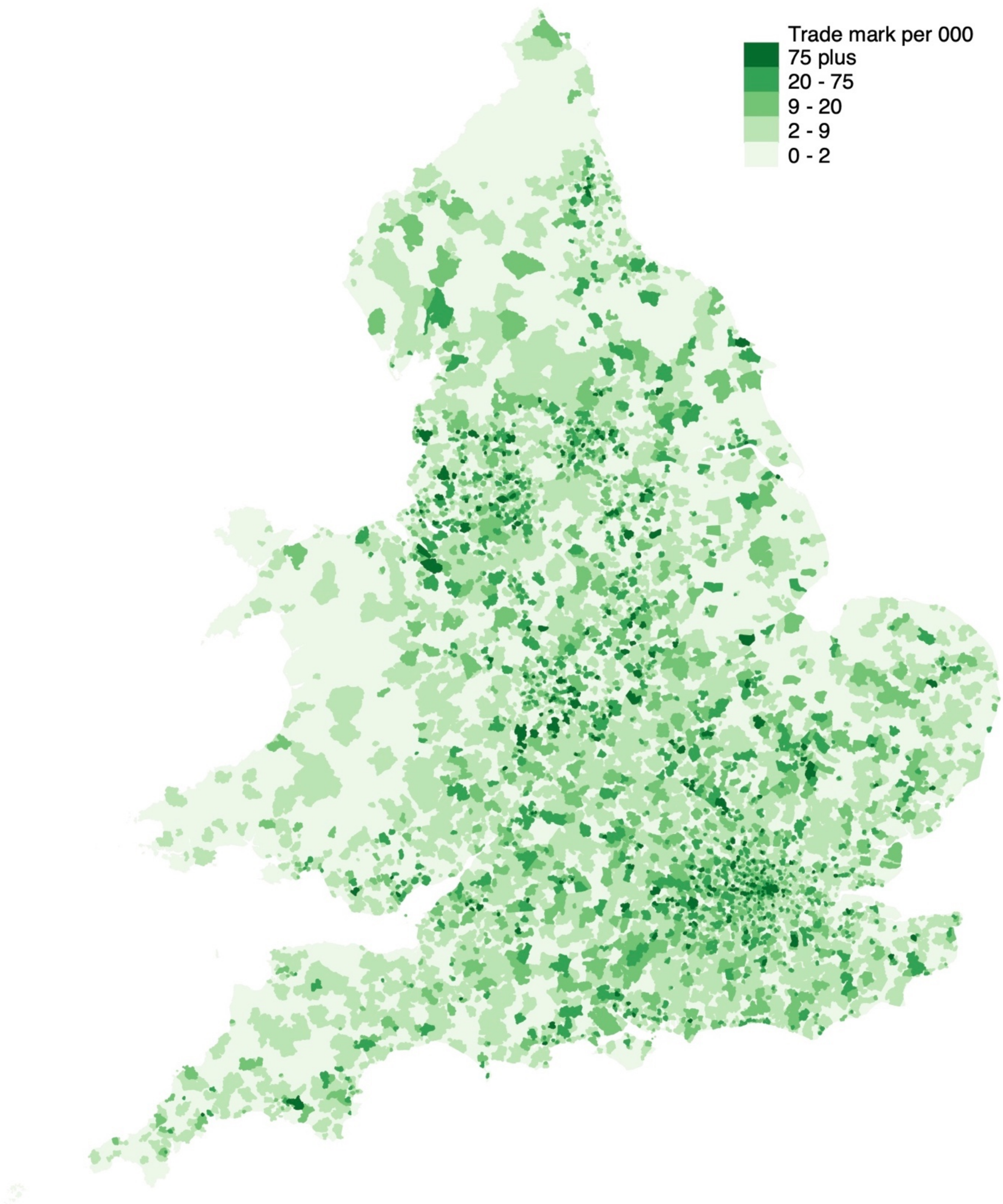


Figure 3: Registered design intensity by LSOA - 2016

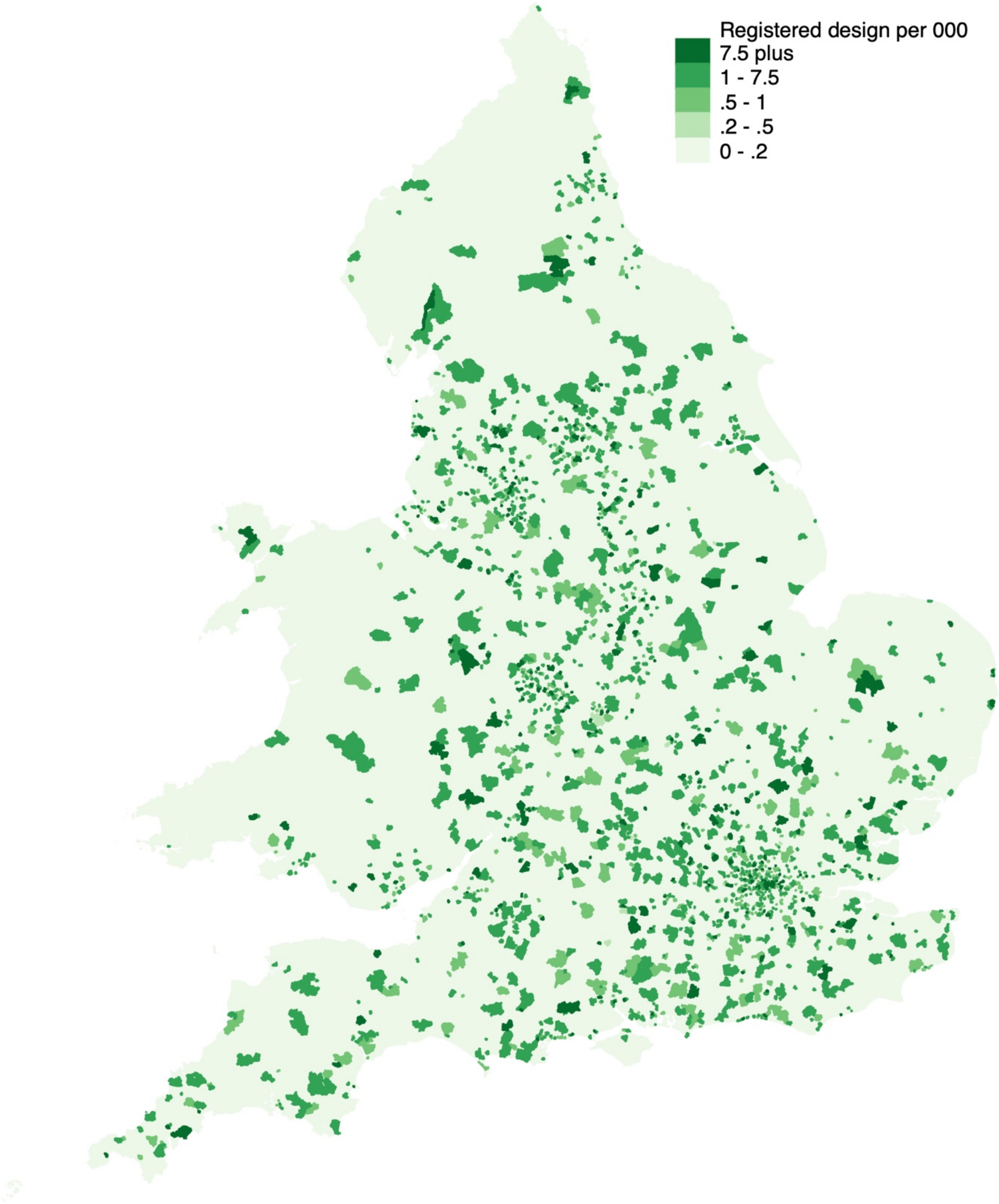


Figure 4: Population density 2015 (per Km²)

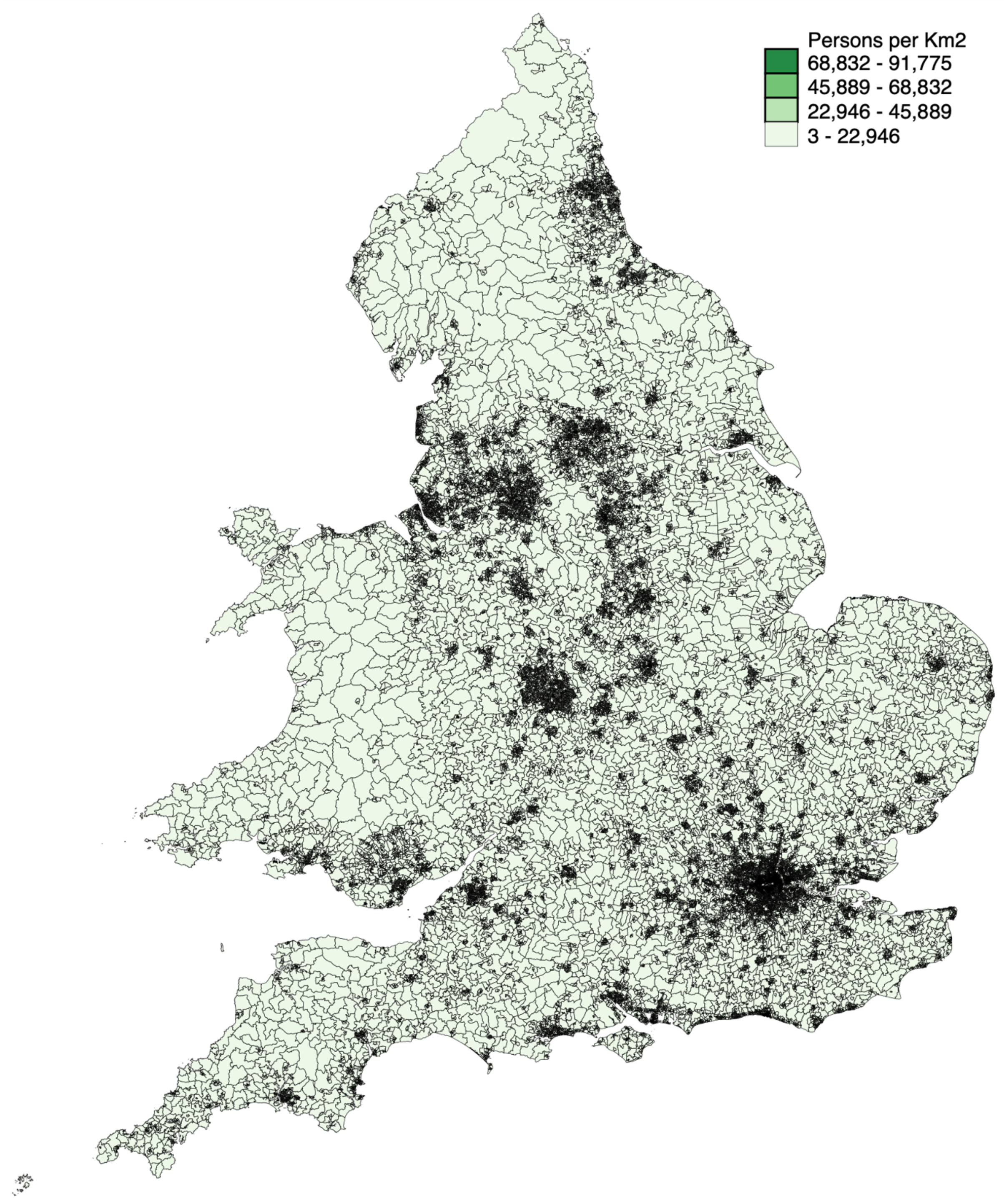


Figure 5: Journey times to nearest town centre - 2015

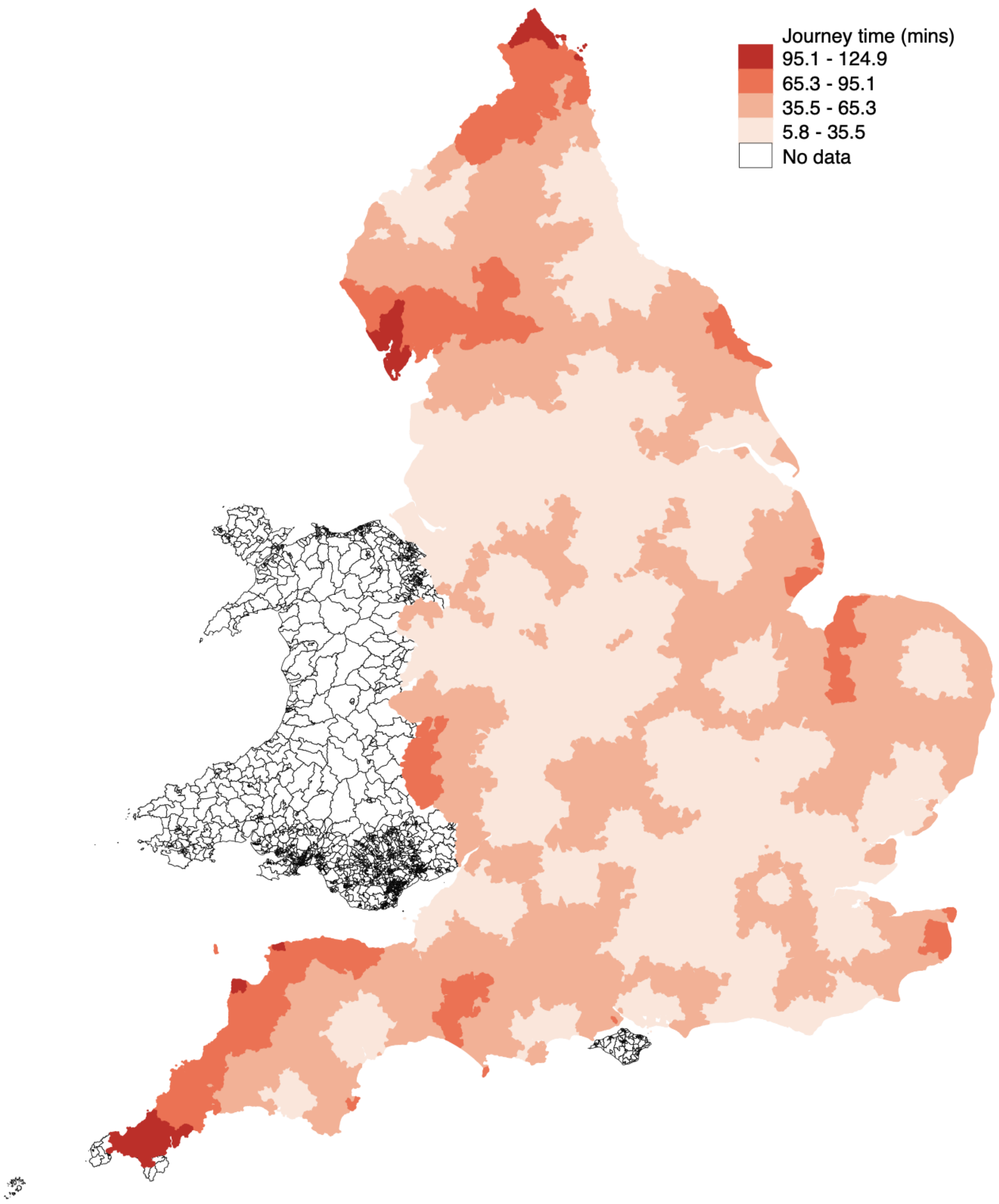
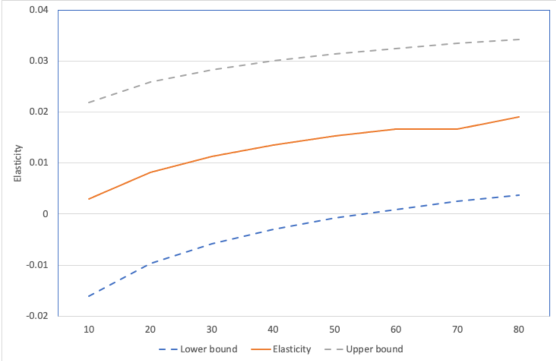
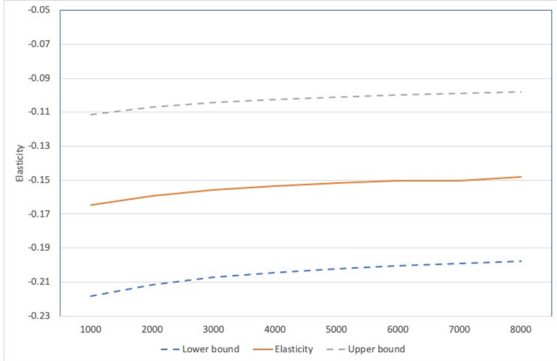


Figure 6: Population and journey time elasticities: 2017

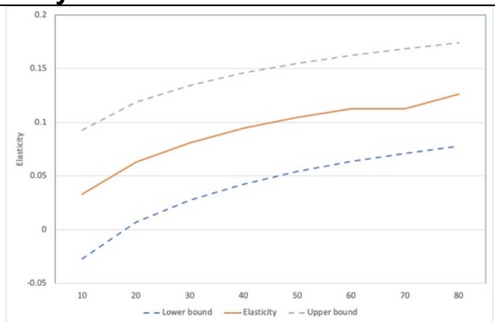
(a) Patents: Population density by journey time



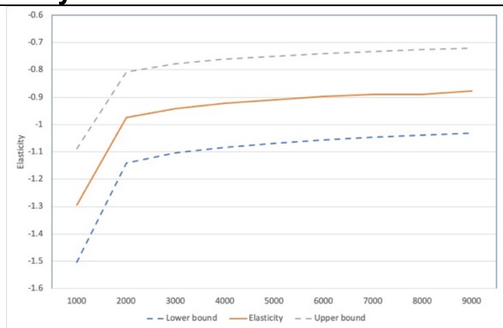
(b) Patents: Journey time by population density



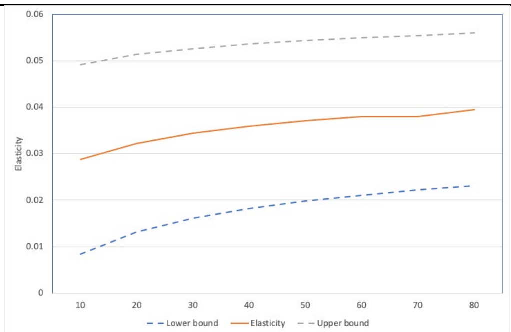
(c) Trade Marks: Population density by journey time



(d) Trade Marks: Journey time by population density



(e) Designs: Population density by journey time



(f) Designs: Journey time by population density

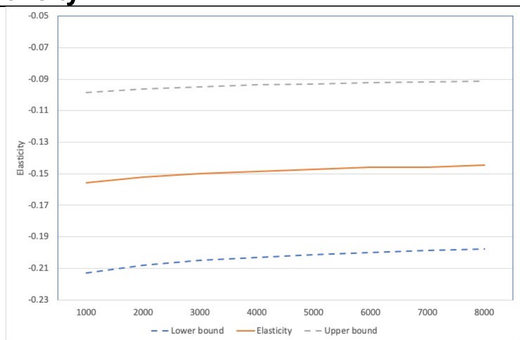
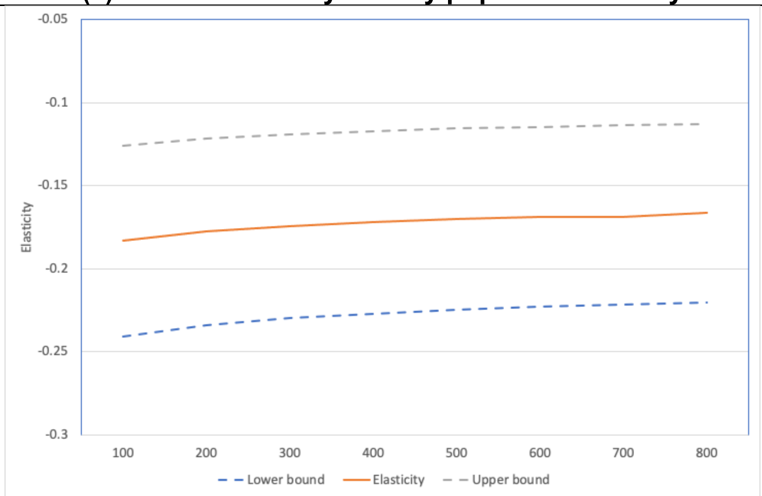
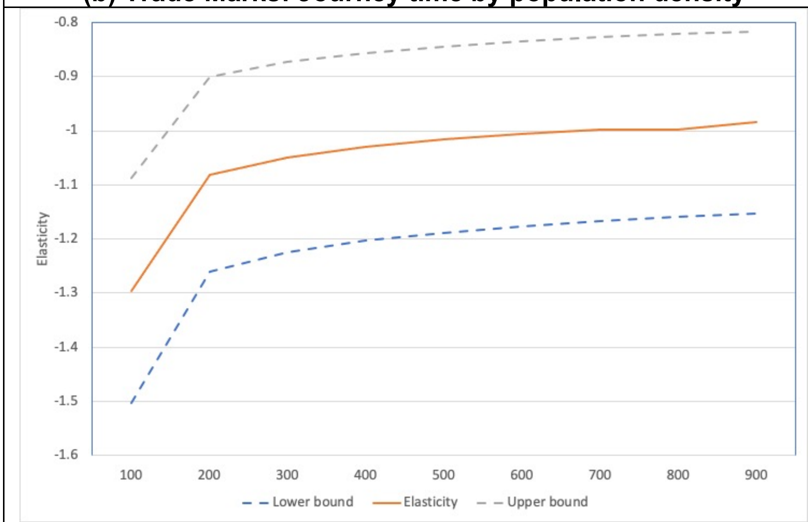


Figure 7: Journey time elasticities at lower population densities: 2017

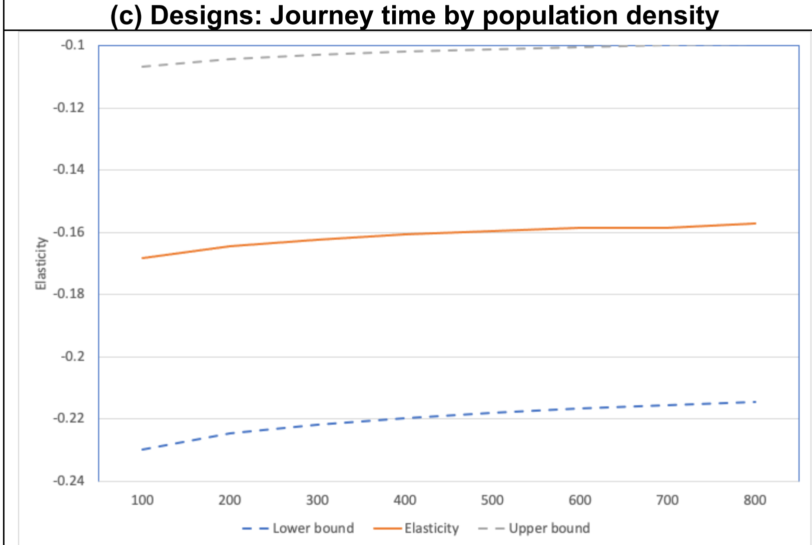
(a) Patents: Journey time by population density



(b) Trade Marks: Journey time by population density



(c) Designs: Journey time by population density



Annex 1: Variable definitions and sources

Variable name	Definition	Sources
Patents (per 000) 2016 and 2017	Live patents held by firms in each LSOA per 000 working age population	Patents: Intellectual Property Office. Working age population: Annual Population Survey
Trade marks (per 000) 2016 and 2017	Live trade marks held by firms in each LSOA per 000 working age population	Trade Marks: Intellectual Property Office. Working age population: Annual Population Survey
Registered designs (per 000) 2016 and 2017	Live registered designs held by firms in each LSOA per 000 working age population	Designs: Intellectual Property Office. Working age population: Annual Population Survey
Population density (ppKm2)	Population density per Km2 in 2015	Office of National Statistics
Journey time (minutes)	Journey time by car to nearest town centre in 2015 (minutes)	Department of Transport
Control variables		
IMD Education domain	Education domain by LSOA 2015	Ministry of Housing, Communities and Local Government
IMD Health domain	Health domain by LSOA 2015	Ministry of Housing, Communities and Local Government
IMD Crime domain	Crime domain by LSOA 2015	Ministry of Housing, Communities and Local Government
IMD Housing domain	Housing domain by LSOA 2015	Ministry of Housing, Communities and Local Government
IMD Environment domain	Environment domain by LSOA 2015	Ministry of Housing, Communities and Local Government
Manufacturing share of employment	Division C over total employment 2015 by LSOA	Business Register and Employment survey, ONS
Business services share of employment	Divisions J, K, L, M, N over total employment 2015 by LSOA	Business Register and Employment survey, ONS

Notes: See text for details of derivation of variables.

Annex 2: Correlation matrix (estimation sample N=32,404)

		1	2	3	4	5	6	7	8	9	10	11	12	13	14	15
1	Patents (per 000) 2016	1.00														
2	Trade marks (per 000) 2016	0.33	1.00													
3	Registered designs (per 000) 2016	0.15	0.19	1.00												
4	Patents (per 000) 2017	0.97	0.31	0.15	1.00											
5	Trade marks (per 000) 2017	0.33	1.00	0.19	0.31	1.00										
6	Registered designs (per 000) 2017	0.15	0.18	0.86	0.15	0.18	1.00									
7	Population density (ppKm2)	-0.09	-0.03	-0.02	-0.09	-0.03	-0.02	1.00								
8	Journey time (minutes)	-0.01	-0.02	0.00	-0.01	-0.02	0.00	-0.11	1.00							
9	IMD Education domain	-0.03	-0.04	-0.01	-0.03	-0.04	-0.01	0.11	-0.11	1.00						
10	IMD Health domain	-0.04	-0.02	-0.01	-0.04	-0.02	0.00	0.23	-0.18	0.71	1.00					
11	IMD Crime domain	-0.04	-0.01	0.00	-0.04	-0.01	0.00	0.39	-0.17	0.48	0.55	1.00				
12	IMD Housing domain	0.03	0.04	0.02	0.02	0.04	0.02	0.14	0.17	0.05	-0.04	0.09	1.00			
13	IMD Environment domain	0.03	0.08	0.02	0.02	0.08	0.03	0.41	0.06	0.11	0.26	0.42	0.25			
14	Manufacturing share of emp.	0.16	0.10	0.05	0.16	0.10	0.05	-0.16	0.02	0.08	0.04	-0.63	0.66	1.00		
15	Business services share of emp.	0.07	0.12	0.03	0.07	0.11	0.03	0.14	-0.01	0.28	-0.27	-0.09	0.10	0.01	-0.14	1.00

Notes: Variable definitions and sources in Annex 1. We exclude around 1 per cent of LSOA areas where patent intensity was particularly high to match the estimation sample in the patent intensity model for 2016.

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