Spatial disparities in SMEs productivity in England

ERC Research Paper 84

February 2020

www.enterpriseresearch.ac.uk

Spatial disparities in SMEs productivity in England

Sara Maioli
sara.maioli@newcastle.ac.uk

Pattanapong Tiwasing
Pattanapong.Tiwasing@newcastle.ac.uk

Matthew Gorton
matthew.gorton@newcastle.ac.uk

Jeremy Phillipson
jeremy.phillipson@newcastle.ac.uk

Robert Newbery
Robert.Newbery@newcastle.ac.uk

Rural Enterprise UK
Centre for Rural Economy & Newcastle University Business School
Newcastle University

The Enterprise Research Centre is an independent research centre which focusses on SME growth and productivity. ERC is a partnership between Warwick Business School, Aston Business School, Queen's University School of Management, Leeds University Business School and University College Cork. The Centre is funded by the Economic and Social Research Council (ESRC); Department for Business, Energy & Industrial Strategy (BEIS); Innovate UK, the British Business Bank and the Intellectual Property Office. The support of the funders is acknowledged. The views expressed in this report are those of the authors and do not necessarily represent those of the funders.

TABLE OF CONTENTS

EXECUTIVE SUMMARY

Improving productivity is critical to increasing economic growth and prosperity in the long-run and a key objective for UK national, regional and local policy. However, a long tail of low productivity businesses and significant spatial variations in productivity characterise the UK economy. This report presents an analysis of the determinants of Small and Medium Sized Enterprise (SME) labour productivity, with a particular focus on how place and productivity interact. The analysis draws on data from the UK Government's Longitudinal Small Business Survey (LSBS) for the years 2015 to 2017. It employs a multilevel regression analysis to understand determinants in enterprise labour productivity in different localities and regions and effectively account for the contextual environment. We applied multilevel analysis to capture the nested structure of our data, modelling a fixed-effects part (at firm level or level one) and a random-effects part at Local Enterprise Partnership (LEP) level (or level two). This allows for the separation of the role of firms' determinants from LEP (sub-regional) effects. To the best of our knowledge, we are the first to apply multilevel analysis to the productivity of firms located in the UK.

Regarding firm-level factors, the results show that microbusinesses and sole traders tend to have lower productivity. In contrast, business capabilities to develop and implement business plans, and obtain external finance, as well as receiving external advice in the previous year, positively contribute to productivity. The sector in which a business operates also matters with health and social work generally associated with lower productivity. Digital capabilities, internal to the SME, as well as some types of network membership contribute to higher productivity. Regarding ownership, after controlling for other factors, the results reveal that family businesses are not more or less productive than non-family ones, but, women-led businesses record significantly lower productivity. At the LEP level, the findings reveal that firms located in LEPs with a more skilled and educated population tend to have higher labour productivity. Improved broadband speeds, in some models, are also associated with higher productivity. Taken together the results give credence, in terms of explaining variations in SME productivity, to industrial organisation theory, the Resource-Based View relating to business capabilities and institutional and network effects.

Not surprisingly, our analysis confirms previous findings from the ONS about the regional disparities in the UK, as we find that firms located in London and the South East demonstrate higher labour productivity. However, we find a lack of supporting evidence for agglomeration theories which stress the benefits of urban areas *per se* in stimulating higher SME productivity, since our analysis shows that firms located in rural areas perform as well as urban firms.

1. INTRODUCTION

Productivity is an important determinant of growth in output, income and living standards, hence it contributes to both industry performance and countries' economic growth. For the UK, the Industrial Strategy (HM Government, 2017) identifies that the level of productivity, measured in terms of output per hour worked, is currently lower than other major European economies, and significantly behind the rest of the G7 economies (ONS, 2018). Improving the UK's low productivity is a key challenge to generate growth in the economy. Small and medium-sized enterprises (SMEs) – defined as those enterprises employing between 0 and 249 employees[1] – are a vital part of the UK economy, accounting for 60% of all jobs and 52% of revenue in the private sector (BEIS, 2019). However, evidence from the Bank of England (Haldane, 2017) reveals that the distribution of SME productivity has a thin upper tail of high-productivity firms and a fat lower tail of low-productivity firms, implying a mode productivity among UK companies about 50% lower than the mean productivity. Boosting SME productivity would have a significant impact on overall UK productivity.

To increase SME productivity, the Industrial Strategy is structured around five foundations of productivity: Ideas, People, Infrastructure, Business environment, and Place. In particular, the disparities in firm productivity are large and growing across sub-regions and regions and have widened since the 2008 global financial crisis (Gal and Egeland, 2018). Performance gaps are also large and persistent not only at the regional level but also across sub-regions and cities (IER, 2016). The spatial disparity in UK productivity is mainly driven by two dimensions: (1) London's outstanding role as a highly productive global city (primarily driven by the financial sector) and (2) a large number of UK regions with low productivity (Gal and Egeland, 2018). These two patterns underpin differences in national productivity as well as the UK economy as a whole, leading to one of the most inter-regionally unequal countries in the industrialised world (Gal and Egeland, 2018; McCann, 2019).

---

[1] Throughout this report we define SMEs as comprising the following categories: zero-employee businesses, microbusinesses (employing between 1 and 9 employees), small businesses (employing between 10 and 49 employees) and medium businesses (employing between 50 and 249 employees).

Evidence from the ONS (2019) suggests that UK productivity, measured as Gross Value Added[2] (GVA) per hour worked, varies spatially across regions and is significantly lower outside of London and the South East. London had the highest level of productivity at 33% above the UK average in 2017, followed by the South East with 8% above the UK average (ONS, 2019). In addition, among the five top performing Local Enterprise Partnerships (LEPs) in terms of productivity, four LEPs were in London (Inner London West, Inner London East, Outer London – West and North West, Outer London – East and North East) and one in the South East (Berkshire, Buckinghamshire and Oxfordshire) (ONS, 2019). Also, considering the rural-urban level using the 2011 Rural-Urban Classification for Output Areas in England, Defra (2019) reports that in 2017 productivity (GVA per workforce job) was highest in Urban with Significant Rural locations at £48,300, followed by Urban with city and town (£48,000) and Urban with major conurbation (£46,800)[3]. However, these levels of productivity are still lower than that of London (£70,900). These regional and sub-regional disparities are dependent on the differences in both firm's internal characteristics and locational effects. Therefore, to reduce gaps in UK productivity and to help understand the key determinants of SMEs' productivity for different types of localities (i.e. sub-regions and regions), an evidence-based analysis of how place and productivity interact is therefore in order.

The objective of this project is to identify the firm and locality (as captured by LEPs) determinants of SME productivity using nested multilevel regression analysis. LEPs are voluntary partnerships between local authorities and businesses, set up in 2011 by the then Department for Business, Innovation and Skills (BIS) to help determine local economic priorities and lead economic growth and job creation within local areas. There were originally 39 LEPs, but Northamptonshire merged with South East Midlands in 2016, reducing the LEPs to 38.

To the best of our knowledge, only a few other recent studies have applied multilevel models to analyse firm productivity or firm performance, allowing the firm-specific and region (or sub-region)-specific variables to be modelled simultaneously to explain the spatial differences. Fazio and Piacentino (2010) and Aiello *et al.* (2014) employed a

---

[2] Global Value Added is a measure of the income generated by businesses less their expenditure.
[3] These GVA figures are based on GVA at broadly county level apportioned at local district level to provide a more refined analysis of GVA across the local authority classification. The figures are also provisional.

multilevel analysis to model spatial disparities in firm labour productivity of Italian firms at provincial and regional level respectively, while Raspe and Van Oort (2011) used multilevel analysis to study the impact of agglomerated knowledge on survival and growth of manufacturing and business services firms in the Netherlands. All three studies find that spatial effects are non-negligible.[4]

Our exploratory study offers what we believe to be the first multilevel analysis applied to the productivity of firms located in the UK. We draw on 2,203 SMEs across England using a panel data from 2015 to 2017 from the Longitudinal Small Business Survey (LSBS) commissioned by BEIS. Our results confirm that firm-specific characteristics such as business size, ownership, and sector significantly affect SMEs' labour productivity. Also, the results report that sub-regional effects have an influence upon labour productivity. Since firms are clustered within LEPs, operating in LEPs with a higher proportion of skilled and better educated population and in a LEP with good digital infrastructure (proxied by broadband speeds) are positively associated with labour productivity.

The report is structured as follows: section 2 reviews briefly the extensive literature on spatial variation in business performance, section 3 discusses the methodology adopted in the empirical analysis, while section 4 describes the secondary data we use to fit our empirical models and present their descriptive statistics. Results from our estimations are presented in Section 5, followed by section 6 concluding with policy recommendations.

2. WHY LOCATION MATTERS: THEORIES OF REGIONAL VARIATIONS IN BUSINESS PERFORMANCE

Analysis to date indicates significant variations in small business performance across regions within developed economies (Reynolds *et al*., 1994; OECD, 2010). These regional variations in small business performance are persistent and particularly pronounced in the UK (Fotopoulos, 2014). The literature relating to spatial variations in small business performance distinguishes between core and non-core regions.

[4] Fazio and Piacentino (2010) considered the provincial socio-economic context, Aiello *et al.* (2014) accounted for regional infrastructure, private R&D intensity, and efficiency of public administration, while Raspe and Van Oort (2011) looked at the urban knowledge context, including innovation and R&D.

Definitions of non-core can relate to an urban–rural dichotomy, whereby urban and rural areas differ in the economic, social, cultural and natural environments for entrepreneurship (Phillipson *et al.*, 2019). They can also relate to a centre–periphery distinction where the latter are lagging regions because of deficiencies in particular capitals (social, financial, human etc.) or their combination (Baumgartner *et al.*, 2013).

In explaining these spatial variations in small business performance, the literature draws largely on four main theoretical perspectives: 1. theories of industrial organisation, 2. the 'New Economic Geography theories', 3. the Resource-Based View (RBV) of the firm and 4. institutional perspectives. In the remainder of this section, we discuss each briefly in turn.

2.1. Theories of Industrial Organisation

The first set of arguments as to why some localities witness weaker small business performance than others relate to their stock of existing businesses possessing adverse characteristics. The most prominent characteristic considered to date is sector, with previous work drawing on theories of industrial organisation (Kaiser and Suzuki, 2006). The latter argues that industries vary in terms of their average rates of return, because of differences in market structure and that opportunities for innovation and technological change vary by sector. Consequently, productivity and productivity-change vary across industries (Syverson, 2011). By this theory, non-core regions suffer from having an adverse industrial profile, with economic activity skewed to the 'wrong' sectors. There is some empirical evidence for this – Curry and Webber (2012) find that variations in productivity across local authority districts relate in part to some possessing a higher proportion of enterprises operating in relatively low–productivity industries. If a region's profile of existing businesses is skewed to sectors with low growth and innovation prospects, it harms subsequent small business start-up and survival rates (Dahl and Reichstein, 2007). Moreover, some sectors, such as professional services, are more amenable to spawning successful new firms than others, such as heavy industries (Acs and Armington, 2004; Armington and Acs, 2002; Anyadike-Danes and Hart, 2006).

In regions characterised by an adverse industry profile, many past policy initiatives sought to foster new enterprise development, but in many cases a high proportion of the firms created appeared to have few advantages in the market, with the emphasis on "quantity" of business start-ups coming at the expense of the "quality" of firms (Greene *et al.*, 2004; Shane, 2009). A danger of such enterprise policies is the creation of large numbers of low-productivity firms in sectors with limited prospects for innovation. Specifically, to avoid a misallocation of public resources, the success of enterprise policies depends on contextual preconditions, in particular a sufficient critical mass in existing activities (R&D, technological knowledge, production know-how, managerial competences); the presence of reliable (new) local actors capable of managing new crucial functions; and the presence of credible and appropriate research and innovation projects (Camagni and Capello, 2013).

2.2 The New Economic Geography: Agglomeration, Proximity and Knowledge Spillovers

According to Porter (1998), industrial agglomeration refers to the geographical clustering of a group of firms and institutions, which are related in terms of specific production and/or economic activities. Marshall (1920) introduced the concept of agglomeration economies, claiming that external economies can be achieved by industrial regionalisation (agglomeration) by promoting the division of specialised producers of intermediate goods in a specific region producing economies of scale, and then generating information spillovers. To explain spatial agglomeration of production activity, Krugman (1991, 1998) provides a more recent theoretical contribution, developing the new economic geography literature. Krugman (1991) provided three possible reasons for firms to cluster: agglomeration provides labour market pooling; a higher degree of industrial agglomeration can support non-trade specialised inputs and improve the level of industrial specialisation; and information spillover in spatially concentrated regions can induce a positive externality on the firms' productivity.

The literature demonstrates the importance of proximity and agglomeration and their relationship to knowledge build-up and diffusion for the success of the individual firm (Cusmano, Morrison, & Pandolfo, 2015). Proximity of firms may generate knowledge spillovers, producing a positive impact on firms that are located in the cluster in terms of their performance and efficiency (Audretsch and Feldman 1996, 2003). Such knowledge spillovers can exist not only in small clusters but also in wider areas, even at a regional level. For example, Audretsch and Lehmann (2005) find that firm growth depends not only upon specific firm characteristics, but also on external characteristics such as location and geographical knowledge spillovers at the regional level.

Knowledge requires education to be built, reproduced and extended. Studies have shown how knowledge and skills are identified to have a positive contribution to economic performance (Krueger and Lindahl, 2001; Sianesi and Van Reenen, 2003). For example, for OECD countries, Sianesi and Van Reenen (2003) identify that education is really productivity-enhancing rather than just a device that individuals use to signal their level of ability to the employer. They also suggest that education provides additional indirect benefits to growth, indicating that type, quality and efficiency of education matter for growth. In the UK, Galindo-Rueda and Haskel (2005) look at the impact of skills on firm performance using the combination of the Annual Business Inquiry (ABI) data about firm performance and the Employers' Skills Survey (ESS) data on workplace skills. They find a positive relationship[5] between skills and productivity, and also report that higher level qualifications have a strong effect on productivity. Webber *et al.* (2007) investigate the effect of skills on labour productivity using cross-sectional data on UK firm-level data. They found that low skill workers have a negative contribution to productivity. Looking at the regional level, Abreu (2018) reports that the high level of skills is positively associated with productivity growth. However, there are also very significant regional variations in skills and educational outcomes among the OECD countries.

2.3. Resource-Based View (RBV)

The RBV argues that firms with distinctive and superior resources and capabilities perform better. Regional variations in small business performance thus stem from spatial differences in the distribution of firm resources and capabilities. Specifically, following the work of Barney (1991), the RBV assumes that distinctive and superior (valuable, rare, inimitable and non-substitutable) resources and capabilities are essential for firms to achieve superior performance. From a RBV perspective, resources are "bundles of tangible and intangible assets, including a firm's management skills, its organisational processes and routines, and the information and knowledge it controls that can be used by firms to help choose and implement strategies" (Barney *et al.*, 2011: 1300). Resources could be, for example, a strong brand name, cooperation among managers and the entrepreneurial ability to integrate factors of production (Alvarez and Barney, 2017). Empirical evidence suggests that in explaining variations in enterprise performance, firm effects are more important than industry effects (McGahan and Porter, 1997; Wiklund and Shepherd, 2003). However, given its focus on factors internal to the firm, the RBV

[5] These results however do not necessarily reflect a direct, causal relationship between workplace characteristics and a firm's performance.

receives widespread criticism that it downplays institutional factors and cannot provide an adequate understanding of the processes and support mechanisms that generate firm-level resources and capabilities (Sheehan and Foss, 2007).

2.4. Institutional Perspectives

Institutional perspectives emphasise that entrepreneurship occurs within a social environment comprised of interdependent actors (Rodríguez-Pose, 2013), where institutions are "systems of established and embedded social rules that structure social interactions" (Hodgson, 2006: p.18). While the RBV focuses on the internal capabilities and resources of the firm (e.g. employee skills and knowledge), institutional perspectives consider the external business environment and, for example, institutions such as universities, schools, business support services and networks that create human capital and its utilisation within entrepreneurial processes (Stam, 2015; Rodríguez-Pose, 2013; Henley, 2018). As institutions are key enablers of innovation, mutual learning and productivity change (Putnam, 2000), regional differences in institutional arrangements lead to spatial variations in small business performance. Specifically, regions produce a distinct pattern of human agency that determines the nature and rate of innovation and growth (Huggins *et al*., 2018). The nature of institutional arrangements or 'thickness' affects the potential for regional development. In understanding the latter's scope, institutional scholars emphasize the density of combinations of institutional capital (knowledge, resources), social capital (e.g. trust, reciprocity), and political capital such as collective action capacity (Rodríguez-Pose, 2013). At the enterprise level, this informs network capital - building and managing relationships beyond market transactions (Huggins *et al.*, 2018). Network capital is central to innovation and growth, as regions require flows of knowledge between agents capable of exploiting market opportunities (Baumgartner *et al.*, 2013; Crespo *et al.*, 2014; Huggins and Thompson, 2015; Huggins and Thompson, 2014).

Network capital appears important for explaining how entrepreneurs identify and exploit opportunities to create new gainful activities (Baumgartner *et al.*, 2013; Huggins and Thompson, 2015). Empirical research suggests that industry-level network membership matters for successful new business formation and growth (Delmar and Shane, 2006), providing established contacts with both suppliers and buyers and a better understanding of industry practices to avoid the mistakes of novices (Renski, 2015). Networks can also generate business ideas, helping entrepreneurs to better understand outstanding problems and the unmet needs of suppliers and buyers through regular contact (Renski, 2015; Delmar and Wennberg, 2010; Newbery *et al.*, 2013). However tacit knowledge is spatially sticky, so that it is not easily spread geographically and may be accessible only through direct physical interaction (Amin and Cohendet, 2005). Consequently, those in non-core regions may be less able to understand the outstanding problems and the unmet needs of suppliers and buyers (Huggins and Thompson, 2015). Network capital lowers uncertainty and information costs, but is likely to be geographically uneven as the generation and transmission of knowledge is 'sticky' in space (Qian *et al*., 2013; Huggins and Thompson, 2014).

Non-core regions may suffer from low levels of network capital where path-dependencies prevail – core regions (whether urban or rural), as hots spots for innovation, further add to their network capital as innovation generates further opportunities for small business formation and growth, and attract additional resources such as financial capital. In contrast, business formation and survival in non-core regions may be skewed to sectors where opportunities for innovation are lower (with low productivity). In other words non-core regions possess fewer and weaker connections because of a lack of proximity to other firms or support services, which may particularly hamper innovation in rural areas (Lee and Rodríguez-Pose, 2013). From a policy perspective, such trends generate calls for aiding non-core regions to develop network-based relationships (Huggins and Thompson, 2014; Huggins *et al.*, 2018). However, questions remain as to the extent to which businesses in non-core regions suffer from a deficit of network capital and the degree to which external agencies can aid growth (Huggins et al., 2018).

Location may be less important in building network capital in an era of digital connectivity. If so, the digital infrastructure, rather than the physical proximity to other firms and stakeholders, becomes increasingly important for the individual firm. The unequal quality of digital infrastructure across regions, however, can contribute again to spatial disparities in firm productivity and performance. Broadband, in particular, plays an increasing role in regional disparities in productivity and economic growth (Czernich *et al.*, 2011; Jordán and De León, 2011; Mack and Faggian, 2013; Gal and Egeland, 2018). A number of studies examined the impacts of broadband and other digital infrastructure on regional performance. For example, Lehr *et al.* (2006) show a positive impact of broadband on economic growth in the US communities. Likewise, Mack and Faggian (2013) also identify that broadband has a positive impact on productivity only in the US counties with high levels of human capital and/or highly skilled occupations. Koutroumpis (2009) also suggests that regions or countries with higher penetration levels of broadband contribute to economic growth in 22 OECD countries. Similarly, Dijkstra *et al*. (2013) identify that improving the access to services, including broadband, can contribute positively to higher growth rates, especially for localities outside of large cities and rural regions in European countries. In the UK, Gal and Egeland (2018) report that access to ICT, including broadband, is positively associated with improved productivity at the regional level.

After reviewing succinctly the literature on spatial disparities in productivity, we now outline the empirical approach taken to analyse LSBS data.

3. EMPIRICAL APPROACH: MULTILEVEL ANALYSIS

To understand enterprise productivity in different localities and regions and effectively account for some level of economic context, we apply a nested multilevel regression analysis (also called mixed-effects or hierarchical analysis). This allows us to model the hierarchical nature of the problem: firms operate within higher-level environments that affect their decisions. These effects are typically uncovered with hierarchically structured data, in the sense that the units (firms) refer to different levels of spatial aggregation (sub-regions or LEPs and regions) and analysed as part of a group of firms located in the same geographical area, since location in which firms operate may affect their performance. In our study, we chose to consider the LEPs as our clustering units. LEPs have been charged by Government to bring together the relevant public, private, voluntary and community bodies in order to promote economic growth (BIS, 2015).

Exploiting the spatial structure of the data allows us to distinguish, in the estimation, the heterogeneity due to individual-specific factors from the heterogeneity due to spatial factors, whose influence may operate both in terms of mean and slope effects (Fazio and Piacentino, 2010; Aiello *et al.*, 2014). Standard regression models such as OLS or GLS, are inappropriate when there exists a hierarchical structure in the data because they do not allow for residual components at each level in the hierarchy and treat the firms as independent observations, so the standard errors of regression coefficients will be underestimated, leading to an overstatement of statistical significance.

Moreover, as discussed in Rasbash *et al.* (2017), a multilevel model (or mixed-effects model as it combines fixed and random effects) is superior compared to the more commonly used fixed-effects alternative because it addresses potential efficiency issues arising in the fixed-effects approach from the irregular distribution of firms across groups, and specifically from the presence of some groups of small size, i.e. in our case LEPs with only a handful of firms (e.g. Tees Valley has only 75 firms compared to London which has between 1,329 and 1,335 depending on the year). It also relaxes the assumption of zero intra-group correlation, crucially important when dealing with economic geography.

In order to allow for the estimation of random-effects models, the number of groups has to be relatively large. A rule-of-thumb says that at least 20 groups should be included (Heck and Thomas, 2000; Hox, 2002; Rebe-Hesketh and Skrondal, 2008). As there are 38 LEPs (following boundary changes), this satisfies such rule and allows us to adopt a two-level analysis where at the first level we have firms that are nested in LEPs at the second level. As England comprises nine regions, rather than adding a third level of analysis, we instead account for variations across regions using fixed-effects (in particular to account for the disproportionate impact of London and the South East, as already mentioned in the introduction).

Adapting the specification from Rebe-Hesketh and Skrondal (2004), Fazio and Piacentino (2010), and Rebe-Hesketh and Skrondal (2012), our multilevel model is a longitudinal two-level model with random intercept and random slopes. Although we allow random slopes, these are for firm-level variables and, as explained below, we do not introduce LEP-level variables with random slopes. The model to be estimated can be expressed as:

$$Y_{ijt} = \beta_{0j} + \sum_{h=1}^{H} \beta_h \mathbf{X}_{it} + \sum_{g=1}^{G} \beta_{gj} \mathbf{W}_{ijt} + \sum_{l=1}^{L} \beta_l \mathbf{Z}_{jt} + \varepsilon_{ijt} \qquad \varepsilon_{ijt} \sim N(0, \sigma_e^2) \qquad (1)$$

where Y_{ijt} is firm's productivity (measured in terms of the natural logarithm of turnover per employee) of *i*-th firm nested within *j*-th LEP; *t* denotes the wave survey, $\mathbf{X}_{it}$ is a vector of H explanatory variables at firm-level, whose β_h coefficients do not change across LEPs; $\mathbf{W}_{ijt}$ is a vector of G explanatory variables for the *i*-th firm, whose β_{gj} coefficients are allowed to vary across LEPs; $\mathbf{Z}_{jt}$ is a vector of L explanatory variables at LEP level (see Table 2), whose coefficients do not change across LEPs. Hence, β_h and and β_l are deterministic coefficients, whilst the intercept β_{0j} and the slope β_{gj} are LEP-specific random coefficients as follows:

$$\beta_{0j} = \gamma_{00} + u_{0j} \qquad u_{0j} \sim N(0, \sigma_{00}^2) \qquad (2)$$

$\beta_{gj}=\gamma_{g0}+u_{gj}\quad u_{gj}\sim N(0,\sigma^2_{g0})$ (3)

and ε_{ijt} is the error term, u_{0j} and u_{gj} are random error terms defined at LEP level with $u_{0j}\sim N(0,\sigma^2_{00})$, and $u_{gj}\sim N(0,\sigma^2_{g0})$, i.e. they are assumed to have a multivariate normal distribution with expectation zero, and to be independent from the residual errors ε_{ijt}. At level 2, the spatial level intercept is specified as the sum of an overall mean (γ_{00}) and a series of random deviations from that mean (u_{0j}). The fixed level-two parameters are presented by γ. We allow for random variations in the slopes of the explanatory variables $\mathbf{W}_{ijt}$ since their coefficient is specified as the sum of a deterministic component (γ_{g0}) and a random component (u_{gj})

This model can be written as one single regression model by substituting Equations 2 and 3 into Equation 1 to allow for random variations in the slopes of some of the explanatory variables, giving the following formulation:

$Y_{ijt}=[\gamma_{00}+\beta_h\mathbf{X}_{it}+\gamma_{g0}\,\mathbf{W}_{ijt}+\beta_l\mathbf{Z}_{jt}]+[u_{0j}+u_{gj}\mathbf{W}_{ijt}+\varepsilon_{ijt}]$ (4)

In (4), labour productivity is assumed to be the result of both fixed effects (first bracket) and random effects (the latter bracket). So the first bracket is the deterministic part of the model, while the second bracket is the stochastic part of the model, because it allows both the intercept and slopes to vary spatially.

When using OLS or GLS, the error terms in (1) are not independently distributed because grouped data violate the assumption of independence of all observations (Mass and Hox, 2005). In (4), we can identify the errors that results from differences across firms or LEPs. The amount of dependence of the errors can be expressed as the intra-class correlation (ICC) which is calculated from an empty model in the multilevel (ML) analysis given by:

$Y_{ijt}=\gamma_{00}+u_{0j}+\varepsilon_{ijt}$ (5)

In (5), Maas and Hox (2005) point out that the model does not explain any variance in Y_{ijt}. It only decomposes the variance of Y_{ijt} into two independent component: the variance σ^2_e, which is the variance of the lowest-level errors ε_{ijt}, and the variance of u_{0j} (σ^2_{00}). Using (4), the ICC can be estimated by the following equation:

$\rho=Var\,(Y_{ijt},Y_{i'jt})=\dfrac{\sigma^2_{00}}{\sigma^2_{00}+\sigma^2_e}$ (6)

It corresponds to the correlation between observations (firms in our case) *i* and *i'* from the same group (or LEP in our case) *j*. The ICC can potentially help to make a decision on whether the multilevel modelling is needed or not, as Equation 6 tells the proportion of the total variance in Y_{ijt} that is accounted for by the clustering. If the ICC approaches zero, that means the observations within groups or clusters are no more similar than observations from different clusters. Then a simple regression should be used.

4. DATA AND DESCRIPTIVE STATISTICS

We use data from the Longitudinal Small Business Survey from 2015 to 2017. The LSBS is a large-scale telephone survey of small business owners and managers across the UK. The survey involves a random sample of firms taken from the Inter-Departmental Business Register and Dun and Bradstreet records, stratified by each UK nation (England, Scotland, Wales and Northern Ireland). The LSBS contains data on firm characteristics, such as firm size, sector, number of employees, and ownership structure. It also includes information on each business's recent performance, obstacles, plans and expectations. The overall sample includes 4,165 enterprises over the three years, of which England accounts for 3,587 records.

Due to data limitations, productivity is measured in terms of turnover per number of employees. This is a weakness compared to a more sophisticated measure of productivity like Gross Value Added per employee, because the latter would also account for a firm's expenditure. Relying only on turnover means that firms operating in activities with relatively higher turnover and/or lower labour intensity (e.g. the financial industry) appear automatically more productive compared to firms operating in activities with relatively lower turnover and/or higher labour intensity (e.g. health and social care). We partially mitigate for this issue by the inclusion of industry dummies as control variables, but more accurate estimations would require analyses at the sectoral level by comparing firms which are all potentially in the same type of activity. This is something that, however, has to be traded off with the ability to undertake spatial analysis, as granular sector-level analyses would limit the number of observations available at the LEP-level, jeopardising the ability to generate statistically meaningful estimates.

Turnover can be calculated using information from two questions in the LSBS survey: actual turnover over the last 12 months; and turnover bands over the last 12 months where firms did not disclose a precise figure (here we used the mid-point of the band indicated by firms). For the firm-level analysis, we include business profile and characteristics as key determinants such as business age, registration, legal status, industrial code, women-led business, capabilities for innovation, obtaining external finance, operational capability, strategic capability, as well as business size (Table 2). At LEP level, we merge LSBS and other datasets through the LEP codes to identify locality-related determinants, including broadband speeds from Ofcom, and the National Vocation Qualification at level 4 (NVQ4)[6] from NOMIS.

The LSBS provides information on the LEP where each firm is located (e.g. this variable is coded LEP1_2015 for 2015), therefore, we merged the LEP variables from the other sources with the LSBS.[7] Table 1 provides the information on the variables used at the LEP level between 2015 and 2017. In the LSBS data, London LEP has the highest number of SMEs with 451 firms, followed by South East LEP (262) and Heart of the South West LEP (172). Using information from the Office of Communications (Ofcom) on broadband speed, which is collected at the LEP level, York, North Yorkshire and East Riding LEP has the highest average percentage of premises that are unable to receive broadband speeds of 2Mbps, which is a basic UK's broadband speed (Department for Digital, Culture, Media and Sport (DCMS), 2019), with 2.01%, followed by Cumbria (1.98%) and Cornwall and Isle of Scilly (1.33%). Many LEPs however have zeros values, implying that no premise located in those LEPs has limited access to fast broadband. Information from the official labour market statistics (NOMIS) on LEP-level population aged 16-64 years who have the National Vocational Qualification at level 4 or above (NVQ4) shows that the average percentage of population at the NVQ4 for Oxfordshire LEP is 50.20%, which is the highest level, followed closely by London (50.07%) and Buckinghamshire Thames Valley (47.93%), but Black Country LEP has only 23.3% of population at NVQ4 level, showing a huge disparity in education attainments across LEPs in England, as shown by the standard deviation value of 7.44 in Table 2 for this variable (compared with a standard deviation for broadband of 0.54). Using the LSBS

[6] NVQ4 are competence-based qualifications at level 4 which involve the application of knowledge and skills in a broad range of complex, technical, or professional work activities performed in a wide variety of contexts and with a substantial degree of personal responsibility and autonomy.
For England, Wales and Northern Ireland the UK Government includes NVQ4 into level 4 qualifications, along with the following: certificate of higher education (CertHE, which corresponds to the first year of a bachelor degree); higher apprenticeship; higher national certificate (HNC); level 4 award; level 4 certificate; level 4 diploma (https://www.gov.uk/what-different-qualification-levels-mean/list-of-qualification-levels).
[7] However, approximately 2,302 firms in 2015 were not linked to LEP information. Given that the data record postcodes without the last three digits, it is not possible to match them with the corresponding LEP.

2015-17, as expected, London LEP has the highest average level of labour productivity measured in terms of turnover per employee (£158,868), followed by Buckinghamshire Thames Valley (£125,414) and Hertfordshire (£123,883), while the lowest labour productivity is found in Tees Valley LEP (£43,560).

Table 2 details descriptive statistics using the LSBS from 2015 to 2017. Approximately 28% of SMEs in England are located in rural areas using the UK Government's rural-urban classification. Eleven per cent of SMEs are located in London and the South East. Approximately 32% of SMEs are a micro business, while around 27% and 17% are a small and medium sized business, respectively. Eighteen per cent of English SMEs operate in the professional/scientific sector, followed by wholesale/retail (14%), and manufacturing (10%). More than 65% are family enterprises, while only 13% and 21% of English SMEs are sole traders and women-led businesses, respectively. The average level of SME productivity in England measured in terms of turnover per total employee is £89,244 with a median of £43,468. The latter figure reflects the predominance of micro- and small-sized businesses in England.

For business capabilities, we find that 48% of SMEs in England have a strong capability for obtaining external finance, 64% for implementing and developing a business plan and strategy, 71% for operational management and 60% for innovation.[8] Additionally, SMEs reported whether they use different types of business networks. More than 50% of English SMEs are members of a social media based business network, with fewer belonging to a local Chamber of Commerce (22%)[9]. These variables were only recorded for 2015. For technology used, more than 80% report that they have their own website, while around 18% use third party websites to promote or sell products or services[10]. For the LEP variables, the average percentage of population aged 16-64 years who have the NVQ4 qualifications for the English SMEs is 37.50%. Also, the average percentage

8 Business capabilities have been surveyed with question F4 in 2015 reading as "How capable would you say your business is at ..." where external finance, business plan and strategy, operational improvement and innovation were then each asked separately. A Likert scale with answers ranging from 1 (very poor) to 5 (very strong) was used to capture the answers. We coded 4 (strong) and 5 as one, and 1-3 as zero in the construction of our capabilities dummies.
9 The LSBS defines a formal business network as one that meets regularly while an informal business network meets socially to discuss mutual business interests.
10 The business capabilities, business networks and technology used were only collected for the year 2015. Thus, to investigate the impact of these variables on productivity, they are assumed to be invariant over the three-year period. This obviously restricts our sample to firms that we can observe at least in year 2015.

of SMEs who are unable to receive broadband speeds of 2Mbit/s for the English LEPs is 0.45%.

5. EMPIRICAL RESULTS

5.1 GLS Model vs. ML Models

We start the empirical analysis from the observation that the LSBS dataset contains many variables that are coded in categorical or binary form. The set of explanatory variables describing the firm's characteristics selected to explain variations in productivity is mostly in such form. The three waves of the LSBS for the period 2015-17 for many variables do not exhibit variation longitudinally (e.g. dummies for rural, women-led business, family business, sole trader, the age of the business coded in bands, whether the firm is a micro- small- or medium-business, etc.). Given the nature of the variables this is unsurprising. Therefore fitting a simple one-level linear regression (where we do not consider the hierarchical structure of the data) means fitting an unbalanced panel data using the Generalised Least Squared (GLS) estimator[11] (which fits a random-effects model), because the fixed-effects (FE) model (which requires the within regression estimator) would drop several variables that do not show variation. There needs to be within-subject variability in variables to properly fit a FE model, otherwise the standard errors may be too large to tolerate. Fitting a GLS regression serves us as a benchmark to test whether the structure of the data allows for a hierarchal analysis when firms are considered not as independent entities (like in the GLS) but are instead 'nested' into LEPs.

The regression results for the GLS estimation are presented in Table 3, under Model 0. Model 0 includes the same sets of variables that will be included in our final model (Model V). We will then adopt the linear regression as model benchmark for comparing the hierarchical or mixed-effects model using Log-likelihood Ratio tests. Table 3 presents the results of the multilevel analysis under models I-V. Model I is regressed without the regressors to identify the errors that result from differences across firms and LEPs. Effectively Model I is an empty regression just for the purpose of showing whether the

[11] The GLS produces a matrix-weighted average of the between-estimated and within-estimated results, where the within estimator or FE, would apply an OLS to the panel data exploiting the variability over time for each panel (firm in our case), whereas the between estimator would fit an OLS exploiting the variability across firms.

introduction of a random intercept at LEP level, in addition to a fixed intercept estimated across all observations, improves the model. Model II only includes the firm-level predictors as listed in Table 2, the time fixed effects and the LEP-level variables broadband and education (NVQ4), which are estimated with fixed-effects, in addition to a random intercept estimated with random effects at LEP level. The idea is to test whether there exists any correlation between the firm-level productivity and broadband accessibility, or the level of education/skills in the LEP where the firm is located. Broadband would inform us whether productivity of firms deteriorates when the proportion of premises in a LEP unable to access fast broadband increases, while the inclusion of education would capture the direct effects of a more skilled workforce that can be directly employed by the firm, and/or the indirect effects due to knowledge spillovers or, say, higher spending power of a more educated workforce[12] that would create positive externalities for the firm. Model II therefore fits a mixed-effects model where, in addition to the variables mentioned, which enter the fixed-effect part of the model, there is also a random intercept being estimated at LEP-level. We notice that the estimated variance of the intercept for this model is 0.008 and significant at 1% level.

Model III augments Model II by adding two random slopes estimated with random effects at LEP level. The variables included are capturing the potential different industrial structure at LEP level. In order to select the most relevant industries, the largest (in absolute value) three significant coefficients for the industry dummies as estimated in Model II were chosen. These were, in order of magnitude, the wholesale and retail (1.270), financial (1.006) and manufacturing (0.980) sectors. After including all three sectors it was noticed that estimated variance of the manufacturing dummy at LEP level was not significant, so only the wholesale and financial dummies were retained. We explored the estimation of additional random slopes for other LEP-level variables (such as the index of multiple deprivation, job density, broadband, business counts, unemployment rate, R&D expenditure, business survival rate) in addition to firm-level variables (like the four different capabilities), but these produced insignificant random-effects parameters. [13]

[12] The correlation between education and the level of Gross Value Added (Balanced) of LEPs is 0.68, in fact quite high.

[13] Education at NVQ4 level or above was also included in the random-effects part of the model, and although its variance was statistically significant, it was too small for the model to produce any meaningful Intra-Class Correlation statistics.

Model IV augments model III with the inclusion of an interaction variable to capture whether the effect of broadband accessibility is different for rural areas.

Finally, Model V augments the fixed-effects part of model IV with the inclusion of the LSE dummy, which captures the London and the South East regions, to allow variation in productivity at regional level for firms located in London and the South East.

The first part of Table 3 presents the estimates for the fixed-effect part of the mixed-effects model, whilst the second part presents the random-effects part with the LEP-level estimates for the variances of the random intercept and slopes. We then present statistics for the Intra-Class correlation (equation 6), which gives the percentage of the total variance of the model explained by the grouping structure of firms by LEPs. Two sets of likelihood-ratio (LR) test are presented. The LR test (one-level) is for comparing each ML model with a one-level linear model to see if there is any benefit in using the multilevel analysis. The LR Test (model II) instead compares models III, IV and V with model II to see if the inclusion of the random slopes estimated at the second level improves the former models compared with the inclusion of only a random intercept estimated at the second level in the latter.

For all models the LR Test (one-level) is statistically significant at 1% level, indicating that using multilevel methodology is required and the intercept should be considered as a LEP-by-LEP variant coefficient. For models III-V the LR Test (Model II) is significant at 1% level, indicating that the coefficients estimated for the financial and wholesale industrial sectors need to be allowed to vary at LEP level as they have a different impact on firms' productivity across LEPs. The Inter-Class Correlation (ICC) indicates that 1.4% (0.014) of SMEs' productivity can be explained by their mere spatial location in the case of model I, whilst for the other models the value reduces to 0.80%, 0.64%, 0.55% and 0.32% respectively. Although the ICC for model I is low compared with Aiello *et al*.'s (2014) result from manufacturing firms in Italy (4.6%) and Raspe and van Oort's (2011) result in the Netherlands (2.3%), we cannot ignore the LEP effect when considering disparities in productivity. One potential reason for the smaller "LEP effect", compared with previous studies of the role of spatial location on productivity, may relate to the nature of the broadband variable. Given the nature of the data available, at the LEP level broadband is measured in terms of the percentage of premises which have access to the basic speed of 2 M/bit per second. Most firms are located in places where this threshold is met, so that discrimination between firms in terms of the digital infrastructure they encounter is limited.

We also present the estimates for the random-effects part of the model, i.e. the variances for the intercept and slopes estimated at LEP level. For model I-III the variance for the intercept estimated at LEP level ranges from 0.015 to 0.006 respectively and it is significant in all three cases at 1%. In model IV and V the variance for the random intercept becomes less significant, being significant at 10% in model IV or insignificant in model V. In the latter case the insignificance is due to the variability of the intercept being picked up by the introduction of a strong fixed effect as the region dummy LSE. Regarding the random slopes, in all three models III-V both the variances associated with the dummies for the wholesale & retail sector and the financial sector show a significance level of 1%. Noticeable is the difference in magnitude of the variances: the financial sector has the highest variance of all with values ranging from 0.604 to 0.653, whereas the wholesale & retails sector shows a range of 0.120-0.125. This again is not surprising, given the geographical concentration of the financial industry in the UK.

Location matters also in terms of industrial structure, as the spatial contribution of some sectors (financial, wholesale and retail but not manufacturing) to productivity changes by LEP. Taking model V, we notice from Table 3 that the fixed-effect coefficient associated with the financial industry and the wholesale/retail sector are 0.653 and 0.125 respectively. From the random effects estimation we can retrieve that the range for this parameters across LEPs goes from 0.606 to +0.662 for the financial industry and from -0.045 to +0.074 for the wholesale/retail industry (these values are not displayed in the table).[14] The value of the fixed-effects intercept for model V is 9.496, but estimating the random-effects variance of the intercept gives a range from -1.768873 to 1.470935 across LEPs.

The high level of significance of the variances estimated for the random intercept and slopes corroborates the notion that a multi-level analysis is beneficial.

Overall, the results from the last four models are similar. We discuss them in the following sections.

---

[14] These are the min and max values of random effects estimated with the Best Linear Unbiased Prediction (BLUP) for linear mixed models.

5.2 Business Size, Age and Ownership

We find that sole traders tend to have lower productivity, and this is statistically significant at 1%. In model II it appears that younger firms (age 0-5 years) also are less productive with a statistical significance of 10%, although this result is not replicated in the other models. For business size, micro businesses are negatively associated with productivity, with a significance level of 10%. However, small and medium businesses have a positive association with productivity, indicating that larger SMEs (small-sized and medium-sized rather than micro-businesses) are significantly more productive, with a statistical significance of 1%.

In terms of enterprise ownership, after controlling for other factors, the results also reveals that family businesses are not more or less productive than non-family ones, but women-led businesses record significantly lower productivity at 1% significance level. The reasons for this are likely to be complex and warrant further investigation.

5.3 Business Capabilities and External Advice

The results indicate that firms that received information or advice in the previous 12 months are significantly more productive (at 5% level).

We also find that strong business capabilities for obtaining external finance (*capability finance*) and for implementing and developing a business plan and strategy (*capability strategy*) give a positive contribution to productivity, with a significance level of 1% associated with these coefficients. Capabilities for developing and introducing new products or services (capability innovation) and for operational improvement (*capability operation*) seem instead to not significantly affect productivity.

5.4 Industrial Sector, Technology and Business Networks.

Additionally, the sectoral composition of the economy matters. Firms operating in the primary, manufacturing, construction, wholesale and retail, transport and storage, food and accommodation, information and communication, financial and real estate, administrative and support, and professional and scientific sector have a positive association with productivity. However, health and social work has a negative relationship with productivity. These findings are in line with theories of industrial organisation (Syverson, 2011), and related empirical evidence (Geroski, 1991), which highlight that productivity varies by industry.

Regarding the technology used, SMEs possessing their own websites are significantly more productive, with a statistical significance of 1% associated with this coefficient; whilst reliance on third-party websites to promote or sell products or service is not associated with productivity in a statistically significant way. Considering business networks, we find that being a member of a local Chamber of Commerce and using a social-media-based business networks are positively associated with productivity, with a statistical significance for both of 10%.

5.5 Human Capital, Broadband and Rurality

Looking at the LEP variables, the findings for education and skills, as measured with NVQ at level 4 or above qualifications, show that firms located in LEPs with a more skilled and educated population tend to have higher labour productivity, and this relationship is significant at 1% level. The coefficients are, however, small, and this may reflect that measuring human capital at the LEP level, while important for capturing differences generally in local labour markets, does not the capture the effect of specific skills on labour productivity at the individual firm level.

The results for digital infrastructure at LEP level show instead more mixed results. The dummy broadband, which captures the proportion of premises located in the LEPs with limited access to broadband speeds of at least 2Mbps, which is a basic UK's broadband service, is positive (as expected, since access to faster broadband should improve productivity) but statistically insignificant in model II and III. However with the introduction of an interaction term capturing whether the impact of broadband is different across rural vs. urban areas, the rural dummy becomes insignificant, whilst the broadband dummy becomes significant at 5% and 1% level respectively in models IV and V. This indicates that broadband speeds can potentially enhance productivity. The reason why the rural variable becomes insignificant in the presence of broadband relates to the relatively high correlation coefficient for these two variables.[15] However at the same time the interaction term shows a positive relationship of broadband for rural firms' productivity in models IV and V, significant at 10% level, meaning that rural firms *un*able to access faster broadband tend to have higher productivity. This last result, although puzzling, is probably associated with the importance of rurality on productivity: whilst firms located

[15] As broadband is defined at LEP level, we calculated the percentage of rural firms out of the total number of firms in each LEP. For example for 2015 the correlation coefficient between broadband and percentage of rural firms is 0.69.

in rural areas are positively associated with productivity in models II and III (with a statistical significance of 5%), in model IV and V (when the interaction term of rural with broadband is introduced) this effect disappears, due to the introduction of such interacted broadband effect. A further explanation lies with the fact that this variable contains lots of zeros (for England we have 3,831 zeros out of a total of 10,585 observations), reflecting a genuine good broadband accessibility across the nation. The presence of many zeros implies that this successful rolling out of broadband across geographical locations makes it less likely to impact significantly on productivity since there is less variability across LEPs in this predictor. Further research on the relationship between broadband availability, speeds and SME productivity is warranted, ideally considering digital connectivity at a more fine-grained firm, rather than LEP, level.

Looking at model V we find that, not surprisingly, regions matters for productivity. In model V the regional effect was included with the dummy LSE showing that firms located in London and the South East have higher labour productivity compared to the rest of England. Our result support the finding of ONS (2016, 2019) in which firms located in London and the South East have higher level of productivity than other firms located outside these areas.

We can now look at Model 0, the GLS estimation. We notice that overall the majority of coefficients are similar to the other models, both in sign and significance terms. However, a few differences exist. The variable support does not appear to be significant when estimated with a one-level regression, whereas it is always consistently significant at 5% when using the multilevel analysis, across all five models. The magnitude and significance for two variables capturing firm size is also different. The variable capturing the microbusiness size shows a much bigger coefficient (-0.199) and significant at 1% level compared to the multilevel models, where this coefficient is around -0.6 and significant at 10%. The variable capturing small businesses, on the contrary, is insignificant and negative for the GLS model but positive and highly significant (at 1% level) in all multilevel models. Also, in the GLS the rural indicator, broadband and their interaction are all insignificant, but in our multilevel models we uncovered how these three variables are somewhat related as in models II and III rural has a positive and significant (at 5%) coefficient while broadband and the interaction term are insignificant, and in models III and IV, which introduce the interaction term, show that rural becomes insignificant but broadband and rural are both significant at 10%. So, although the results are to some extent similar, they also reveal interesting differences. We can therefore conclude that using one- or multi-level analysis do not always provide us with the same set of estimates.

6. CONCLUSION

The UK displays large regional disparities in productivity and business growth with a large gap between London and most other regions. Therefore, to understand the role of location on differences in productivity, this paper examines the spatial determinants of individual-level firm's characteristics and contextual-level (sub-regional) determinants of labour productivity.

This analysis is derived from data for 2,203 English SMEs surveyed between 2015 and 2017 as per the LSBS, giving us an unbalanced panel of 5,831 firm-year observations to analyse. We apply the multilevel analysis to deal with hierarchically structured data where the firms are nested in Local Enterprise Partnership areas. This allows for the separation of the role of firms' determinants from LEP drivers of productivity. The multilevel analysis comprises a fixed-effects part (at firm level or level one) and a random-effects part (at LEP level or level two). The flexibility of such mixed-effects estimation allows for the introduction of firm-level and LEP-variables, whose estimated coefficients are fixed, i.e. do not change spatially across LEPs, in addition to spatially-changing variables across LEPs (in our case both the intercept of the model and the effects associated with the financial and wholesale and retail sectors). The two-level analysis was complemented with the introduction of regional effects, introducing a dummy for London and the South East in the fixed-effects part of the model, and showing that when estimating the firm-level productivity spatially differences exist at both LEP and region level.

Our findings confirm that firm-specific characteristics highly affect SMEs' productivity. The findings show that larger SMEs (small-sized rather than micro-businesses) are significantly more productive, while sole traders are significantly less productive. Younger firms tend to have lower productivity, as shown in model II, although this result is not robust across all models. This weakly supports theories regarding the uncertainties of start-up and the role of learning by doing for achieving productivity gains (Tiwasing *et al.*, 2019).

The sectoral composition of the economy matters for SMEs' productivity. The results demonstrate that the health and social work industry is negatively associated with productivity. This industry requires more support and investment in training and development for all skill levels (Forth and Rincon-Aznar, 2018). Also, women-led businesses record significantly lower productivity. This could be partially explained by the fact that women-led businesses are skewed to fields where low paid jobs proliferate such as health and social care (BEIS, 2018), which are traditionally female occupational sectors (Carter *et al.*, 2013). However, some non-sector related factors may also be important to that. Further research could explore the challenges and opportunities in these businesses, disentangling sector and non-sector related determinants.

We also find that digital choices are important, as SMEs that have their own website are significantly more productive, whereas using third-party websites to promote or sell products or services is not statistically associated with labour productivity. Firms also benefit by being networked, as the evidence shows that being a member of a local Chamber of Commerce or using social media networks improves somewhat productivity.

Not surprisingly, our analysis confirms the regional disparities in the UK, as we find that firms located in London and the South East demonstrate higher labour productivity.

Interesting insights come from the impact of LEP variables. SMEs located in LEPs with higher proportions of high-skilled population (measured with NVQ at level 4 or above qualifications) are positively associated with higher labour productivity. This results supports the entrepreneurship and economics theories which stress that proximity to a higher-skilled workforce improves a firm's performance. This highlights the importance of upskilling and retraining of the population. Spatial variations in educational attainment are striking and little progress has been made in recent years to reduce this gap (Education Policy Institute, 2019). Appropriate investment in schools, further and higher education institutions, will be important, especially in a fast-paced environment of technological changes where the adoption of new technology and realisation of high-value production requires highly educated workers. Investments in human capital, while integral to improving long-term firm and regional productivity, may not have a positive short-term effect (Black and Lynch, 1996). Consequently, some other determinants, identified in the analysis, such as support to businesses in setting up their own website and networking with others, may yield greater short-term rewards.

The analysis presents some evidence that SMEs located in LEPs with broadband speeds of at least 2Mbit/s also realise higher labour productivity, proving that digital infrastructure also matters. However, disparities in average broadband speeds at LEP level are less striking than in the case of educational attainment, with broadband a less robust predictor of productivity improvements. Still, completing the rolling out of fast broadband across all locations seems important to boost productivity.

We find a lack of supporting evidence for agglomeration theories which stress the benefits of urban areas *per se* in stimulating higher SME productivity, since our analysis shows that firms located in rural areas perform as well as urban firms. This is in keeping with other analysis, that, when discounting London, differences in performance between urban and rural located SMEs in England are often insignificant (Phillipson *et al.* 2019), albeit with both types of location characterised by a fat, lower tail of low-productivity firms.

Finally, we recognise the limitations of this study and present several suggestions for further research. This study focused on labour productivity (measured by turnover per employee) only, but there are several other measures of productivity that could be adopted depending on data availability: rather than using turnover, value added could be used; rather than dividing turnover or value added by the number of employees, these could be divided by the number of worked hours (better accounting for part-time workers and atypical job contracts). If data on capital and intermediate inputs were available, then total factor productivity could also be calculated. Our analysis could also be improved with the inclusion of more contextual variables at LEP level. We focused on education and good broadband accessibility as we found several other LEP-level variables insignificant but also some other indicators which we would have wanted to use were not available (e.g. the Gross Value Added per Head[16]). In addition to estimating a random intercept (effectively allowing the constant component of productivity estimated at firm-level to vary by LEP), this study only allowed the random slopes estimation for the sector dummies related to the financial sector and the wholesale and retail sector, in a very aggregate way. More granular analysis using more disaggregated industry dummies would shed greater light on crucial industries for the Industrial Strategy (like creative industries, life science, advanced manufacturing). Although we undertook some explorations, the estimation of random slopes for other firm- or LEP-level variables could be investigated further.

We conducted the analysis only for England. To the best of our knowledge, we are the first to apply multilevel analysis to the productivity of firms located in the UK. Extending

16 The ONS is however preparing to publish the GVA per Head at LEP level in the near future.

this type of analysis also to the other three UK nations and to all types of firms, not just SMEs, possibly using alternative measures of productivity, would deepen our understanding and depict a more complete picture about spatial differences of firm productivity in the UK.

REFERENCES

Abreu, M. (2018). 'Skills and Productivity', Evidence Review, *ESRC Productivity Insights Network PIN-08*. (Access 20 April 2019).

Acs, Z. J. and Armington C. (2004). 'Employment Growth and Entrepreneurial Activity in Cities', *Regional Studies* 38, pp. 911-927.

Aiello, F., Pupo V. and Ricotta F. (2014). 'Explaining Total Factor Productivity at Firm Level in Italy: Does Location Matter?', *Spatial Economic Analysis*, 9(1), pp.51-70.

Akaike, H. (1974). 'A New Look at the Statistical Model Identification', *IEEE Transactions on Automatic Control*, 19(6), pp.716-723.

Anyadike-Danes M and Hart M. (2006). 'The impact of Sector, Specialisation, and Space on Business Birth Rates in the United Kingdom: a Challenge for Policy?', *Environment and Planning C: Government and Policy,* 24, pp. 815-826.

Alvarez, S. A. and Barney J .B. (2017). 'Resource-Based Theory and the Entrepreneurial Firm', in: Hitt MA, Ireland D, Camp M, *et al.* (eds) *Strategic Entrepreneurship.* Chichester: Wiley, pp. 89-105.

Amin, A. and Cohendet, P. (2005). 'Geographies of Knowledge Formation in Firms', *Industry and Innovation*, 12(4), pp. 465-486.

Armington, C. and Acs Z. J. (2002). 'The Determinants of Regional Variation in New Firm Formation', *Regional Studies* 36, pp. 33-45.

Audretsch, D. B. and Lehmann E. E. (2005). 'Does the Knowledge Spillover Theory of Entrepreneurship Hold for Regions?', *Research Policy*, 34, pp. 1191–1202.

Audretsch, D. B. and Feldman M. P. (1996). 'R&D Spillovers and the Geography of Innovation and Production', *The American Economic Review, 86*(3), pp. 630–640.

Audretsch, D. B. & Feldman M. P. (2003). 'Knowledge Spillovers and the Geography of Innovation' in J. Vernon Henderson & J. Thisse (Eds.), *Handbook of Urban and Regional Economics, Vol. 4*. Amsterdam: North Holland Publishing.

Barney J. (1991). 'Firm Resources and Sustained Competitive Advantage', *Journal of Management*, 17, pp. 99-120.

Barney J. B., Ketchen D. J. and Wright M. (2011). 'The Future of Resource-Based Theory: Revitalization or Decline?', *Journal of Management*, 37, pp. 1299-1315.

Baumgartner D., Pütz M. and Seidl I. (2013). What Kind of Entrepreneurship Drives Regional Development in European Non-core Regions? A Literature Review on Empirical Entrepreneurship Research', *European Planning Studies*, 21, pp. 1095-1127.

BEIS (2018). *Business Population Estimates for the UK and Regions 2018*, Department for Business, Energy and Industrial Strategy.

BEIS (2019). *Business population estimates for the UK and regions 2019*, Department for Business, Energy and Industrial Strategy.

BIS (2015). *Mapping Local Comparative Advantage in Innovation: Framework and Indicators*, Department for Business Innovation and Skills.

Black, S.E. and Lynch, L.M. (1996). 'Human-Capital Investments and Productivity', *The American Economic Review*, 86(2), pp. 263-267.

Camagni R. and Capello R. (2013). 'Regional Innovation Patterns and the EU Regional Policy Reform: Toward Smart Innovation Policies', *Growth and Change*, 44, pp. 355-389.

Carter, S., Ram M., Trehan K. and Jones T. (2013). 'Diversity and SMEs', *Enterprise Research Centre White Paper* No. 3 (Accessed 16 April 2019).

Czernich, N., Falck O., Kretschmer T. and Woessman L. (2011). 'Broadband Infrastructure and Economic Growth", *The Economic Journal*, 121(552), pp. 505-532.

Crespo, J., Suire R. and Vicente J. (2014). 'Lock-in or Lock-out? How Structural Properties of Knowledge Networks Affect Regional Resilience', *Journal of Economic Geography*, 14, pp. 199-219.

Curry, N. and Webber D. J. (2012). 'Economic Performance in Rural England', *Regional Studies*, 46, pp. 279-291.

Cusmano, L., Morrison A. and Pandolfo E. (2015). 'Spin-off and Clustering: a Return to the Marshallian District', *Cambridge Journal of Economics*, 39(1), pp. 49–66.

Dahl M. S. and Reichstein T. (2007). 'Are You Experienced? Prior Experience and the Survival of New Organizations. *Industry and Innovation*, 14, pp. 497-511.

DCMS (2019). *Building Digital UK: Details of the Plan to Achieve a Transformation in Broadband in the UK*, Department for Digital, Culture, Media and Sport (accessed 1st June 2019.

DEFRA (2019). *Rural productivity and Gross Value Added (GVA) statistics: Productivity levels in rural and urban areas in England* (Accessed: 9 August 2019).

Delmar, F. and Shane S. (2006). 'Does Experience Matter? The Effect of Founding Team Experience on the Survival and Sales of Newly Founded Ventures', *Strategic Organization*, 4, pp. 215-247.

Delmar, F. and Wennberg K. (2010). *Knowledge Intensive Entrepreneurship: The Birth, Growth and Demise of Entrepreneurial Firms*: Edward Elgar Publishing Limited.

Dijkstra, L., Garcilazo E. and McCann P. (2013). 'The Economic Performance of European Cities and City Regions: Myths and Realities", *European Planning Studies*, 21(3), pp.334-354.

Education Policy Institute (2019). *Education in England: Annual Report 2019*. London: Education Policy Institute.

Fazio, G. and Piacentino D. (2010). 'A Spatial Multilevel Analysis of Italian SMEs' Productivity', *Spatial Economic Analysis*, 5(3), pp. 299-316.

Forth, J. and Rincon-Aznar A. (2018). *Productivity in the UK's low-wage industries: a comparative cross-country analysis*, Joseph Rowntree Foundation.

Fotopoulos G. (2014). 'On the Spatial Stickiness of UK New Firm Formation Rates', *Journal of Economic Geography*, 14, pp. 651-679.

Gal, P. and Egeland J. (2018). 'Reducing Regional Disparities in Productivity in the United Kingdom', *OECD Economics Department Working Papers*, No. 1456, Paris: OECD Publishing.

Galindo-Rueda, F. and Haskel J. (2003). 'Skills, Workforce Characteristics and Firm-level Productivity in England', Report prepared for DTI, DfES and ONS.

Geroski, P.A. (1991). 'Innovation and the Sectoral Sources of UK Productivity Growth', *The Economic Journal*, 101(409), pp. 1438-1451.

Greene, F. J., Mole K. F. and Storey D. J. (2004). 'Does More Mean Worse? Three Decades of Enterprise Policy in the Tees Valley', *Urban Studies*, 41, pp. 1207-1228.

Haldane, A. G. (2017). "Producitivity Puzzles", speech given to the London School of Economics, 20th March, Bank of England.

Heck, R. H. and Thomas, S. L. (2000). *An Introduction to Multilevel Modeling Techniques*, Lawrence Erlbaum Associates.

Henley A. (2018). *Small Business Growth and Productivity*. Sheffield: Productivity Insights Network.

HM Government (2017). *Industrial Strategy: Building a Britain* Fit *for the Future*. London: HM Government.

Hodgson, G. M. (2006). 'Economics and institutions', *Journal of Economic Issues*, 40, pp. 1-25.

Hox, J. J. (2002). *Multilevel Analysis: Techniques and Applications,* Mahwah, NJ, Lawrence Erlbaum Associates.

Huggins R. and Thompson P. (2014). 'A Network-Based View of Regional Growth', *Journal of Economic Geography*, 14, pp. 511-545.

Huggins R. and Thompson P. (2015). 'Entrepreneurship, Innovation and Regional Growth: A Network Theory', *Small Business Economics*, 45, pp. 103-128.

Huggins R., Waite D. and Munday M. (2018). 'New Directions in Regional Innovation Policy: a Network Model for Generating Entrepreneurship and Economic Eevelopment', *Regional Studies*, 52: 1294-1304.

IER (2016). *The Northern Powerhouse Independent Economic Review: Final Executive Summary Report*, Segal Quince Wicksteed Partnership.

Jordán, V. and De León O. (2011). 'Broadband and the Digital Revolution', in *Fast-Tracking the Digital Revolution: Broadband for Latin America and the Caribbean*, eds. V. Jordán and H. Galperín. Santiago, Chile: United Nations, pp. 13–48.

Kaiser H. M. and Suzuki N. (2006). *New Empirical Industrial Organization and the Food System*, New York: Peter Lang.

Koutroumpis, P. (2009). ''The Economic Impact of Broadband on Growth: A Simultaneous Approach'', *Telecommunications Policy*, 33, pp. 471–85.

Krueger, A.B. and Lindahl, M. (2001). 'Education for Growth: Why and for Whom?', *Journal of Economic Literature*, 39(4), pp. 1101-1136.

Krugman, P. (1991). 'Increasing Returns and Economic Geography', *Journal of Political Economy*, 99, pp. 483-499.

Krugman, P. (1998). 'What's New About the New Economic Geography?', *Oxford Review of Economic Policy*, 14, pp. 7-17.

Lee. N. and Rodríguez-Pose A. (2013). 'Original Innovation, Learnt Innovation and Cities: Evidence from UK SMEs', *Urban Studies*, 50, pp. 1742-1759.

Lehr, W. H., Osorio C. A., Gillett S. E. and Sirbu M. A. (2006). "Measuring Broadband's Economic Impact", *ESD Working Paper 2006-02*, Massachusetts Institute of Technology. Engineering Systems Division.

Mack, E. and Faggian A. (2013). "Productivity and Broadband: The Human Factor." *International Regional Science Review*, 36(3), pp. 392–423.

Marshall, A. (1920). *Principles of Economics*, London: Macmillan.

Mass, J. C. and Hox J. J. (2005). 'Sufficient Sample Sizes for Multilevel Modeling'. *Methodology*, 1, pp. 86-92.

McCann, P. (2019). 'Perceptions of Regional Inequality and the Geography of Discontent: Insights from the UK', *Regional Studies*, pp. 1–12.

McGahan A. M. and Porter M. E. (1997). 'How Much Does Industry Matter, Really?', *Strategic Management Journal*, 18, pp. 15-30.

Newbery R, Sauer J, Gorton M, Phillipson, J. and Atterton, J. (2013). 'Determinants of the Performance of Business Associations in Rural Settlements in the United Kingdom: An Analysis of Members' Satisfaction and Willingness-to-Pay for Association Survival', *Environment and Planning A*, 45, pp. 967-985.

OECD (2010). *SMEs, Entrepreneurship and Innovation*. Paris: The Organisation for Economic Co-operation and Development.

ONS (2016). *A Review of Regional and Sub-Regional Productivity Statistics: April 2016*, London: Office for National Statistics.

ONS (2018). *International comparisons of UK productivity (ICP), final estimates: 2016*, London: Office for National Statistics.

ONS (2019). *Regional and sub-regional productivity in the UK: February 2019*, London: Office for National Statistics.

Phillipson J, Tiwasing P, Gorton M, Maioli, S., Newbery, R. and Turner, R. (2018). 'Shining a Spotlight on Small Rural Businesses: How Does Their Performance Compare with Urban?' *Journal of Rural Studies*, 68, pp. 230-239.

Porter, M. (1998). *On Competition*. Boston: Harvard Business School Press.

Putnam, R. D. (2000). 'Bowling Alone: America's Declining Social Capital', in: Crothers L. and Lockhart C. (eds) *Culture and Politics: A Reader.* New York: Palgrave Macmillan US, 223-234.

Qian, H., Acs Z. J. and Stough R. R. (2013.) 'Regional Systems of Entrepreneurship: the Nexus of Human Capital, Knowledge and New Firm Formation', *Journal of Economic Geography*, 13, pp. 559-587.

Rabe-Hesketh, S. and Skrondal, A. (2004). *Generalized latent variable modeling: Multilevel, longitudinal, and structural equation models*, Chapman and Hall/CRC.

Rabe-Hesketh, S. and Skrondal, A. (2008). *Multilevel and Longitudinal Modeling Using Stata*. 2nd ed. College Station, TX, Stata Press.

Rabe-Hesketh, S. and Skrondal, A. (2012). *Multilevel and Longitudinal Modeling Using Stata, Vol. II: Categorical Responses*. Texas: Stata Press.

Rasbash, J., Steele F., Browne W.J. and Goldstein H. (2017). *A User's Guide to MLwiN, v3.01*, Centre for Multilevel Modelling, University of Bristol.

Raspe, O. and van Oort, F. (2011). 'Growth of New Firms and Spatially Bounded Knowledge Externalities', *The Annals of Regional Science*, 46(3), pp. 495-518.

Renski, H. (2015) 'Externalities or Experience? Localization Economies and Start-up Business Survival', *Growth and Change*, 46, pp. 458-480.

Reynolds, P., Storey, D. J. and Westhead, P. (1994). 'Cross-National Comparisons of the Variation in New Firm Formation Rates', *Regional Studies*, 28, pp. 443-456.

Rodríguez-Pose, A. (2013). 'Do Institutions Matter for Regional Development?', *Regional Studies*, 47, pp. 1034-1047.

Shane, S. (2009). 'Why Encouraging More People to Become Entrepreneurs is Bad Public Policy', *Small Business Economics*, 33, pp. 141-149.

Sheehan, N.T. and Foss N. J. (2007). ‘Enhancing the Prescriptiveness of the Resource-Based View through Porterian Activity Analysis’, *Management Decision*, 45, pp. 450-461.

Sianesi, B. and Reenen J. V. (2003). ‘The Returns to Education: Macroeconomics’, *Journal of Economic Surveys*, 17(2), pp. 157-200.

Stam, E. (2015). ‘Entrepreneurial Ecosystems and Regional Policy: A Sympathetic Critique’, *European Planning Studies*, 23, pp. 1759-1769.

Syverson, C. (2011). ‘What Determines Productivity?’, *Journal of Economic Literature*, 49, pp. 326-365.

Tiwasing, P., Gorton, M., Phillipson, J., Maioli, S. and Newbery, R. (2019). *Spatial Variations in SME Productivity*, ESRC Productivity Insights Network. (Access 20 April 2019).

Webber, D., Boddy, M. and Plumridge A. (2007). ‘Explaining Spatial Variation in Business Performance in Great Britain’, *The European Journal of Comparative Economics*, 4(2), pp. 319-332

Wiklund, J. and Shepherd D. (2003). ‘Knowledge-Based Resources, Entrepreneurial Orientation, and the Performance of Small and Medium-Sized Businesses’, *Strategic Management Journal*, 24, pp. 1307-1314.

Table 1 - Descriptive Statistics for the LEP Variables, 2015 - 2017

LEPs by region	Number of Business	Productivity (£)	Broadband speeds (Mean of % of premises unable to receive 2Mbit/s)	National Vocational Qualification - level 4 (NVQ4) (%)
North East				
North Eastern	75	63,856	0.41	31.57
Tees Valley	25	43,560	0.76	30.43
North West				
Cumbria	44	77,699	1.98	31.13
Lancashire	82	94,281	0.11	31.67
Liverpool City Region	56	75,518	0.07	30.72
Greater Manchester	106	85,632	0.15	34.44
Cheshire and Warrington	68	71,029	0.79	40.93
Yorkshire and the Humber				
York, North Yorkshire and East Riding	53	79,148	2.01	37.63
Leeds City Region	131	70,715	0.35	32.17
Humber	36	107,580	0.82	29.43
Sheffield City Region	82	56,106	1.00	30.63
East Midlands				
Derby, Derbyshire, Nottingham and Nottinghamshire	125	63,356	0.38	32.30
Leicester and Leicestershire	71	89,918	0.10	32.40
South East Midlands	118	91,822	0.63	35.47
East of England				
Greater Lincolnshire	73	68,457	1.28	27.33
Greater Cambridge and Greater Peterborough	121	82,660	0.97	37.30
New Anglia	147	71,590	1.08	30.97
West Midlands				
Black Country	48	72,352	0.00	23.30
Greater Birmingham and Solihull	87	72,416	0.02	32.23
Stock-on-Trent and Staffordshire	65	68,682	0.35	30.27
The Marches	52	85,037	1.65	32.20
Coventry and Warwickshire	53	45,334	0.45	36.89
Worcestershire	31	53,524	1.01	37.73
South West				
Gloucestershire	68	75,770	1.26	39.42
West of England	91	67,773	0.81	45.07
Swindon and Wiltshire	73	86,344	1.15	37.94
Dorset	60	75,897	0.50	35.61
Heart of the South West	174	63,240	0.48	35.70
Cornwall and Isle of Scilly	73	61,565	1.33	32.07
South East and London				
Hertfordshire	57	123,883	0.46	42.53
Buckinghamshire Thames Valley	33	125,414	0.55	47.93
Oxfordshire	70	84,822	0.21	51.20
London	453	158,868	0.00	51.07
Thames Valley Berkshire	60	119,063	0.65	46.59
Enterprise M3	139	113,803	0.00	44.36
South East	26	81,790	0.22	32.20
Coast to Capital	127	53,776	0.43	43.56
Solent	76	69,016	0.30	33.94
Total	3,571			

Note: Avg. is the average value

Table 2 - Definition of the variables used in the analysis

Variable	Definition	English SMEs		
		Obs.	Mean	SD
Dependent				
PRODUCTIVITY	Turnover per employee (continuous) (pound sterling (£)), 2015-2017, in natural log	3,502	89,244.05	296513.7
Firm-level				
RURAL	Business is located in rural areas, 2015-2017(1=Rural areas, 0=Urban areas)	3,585	0.28	0.45
FAMILY	Whether a firm is a family owned business, 2015-2017 (1=Yes, 0=Otherwise)	3,570	0.66	0.48
MICRO	Whether a firm has 1-9 employees, 2015-2017 (1=Yes, 0=Otherwise)	3,587	0.32	0.47
SMALL	Whether a firm has 10-49 employees, 2015-2017 (1=Yes, 0=Otherwise)	3,587	0.27	0.45
MEDIUM	Whether a firm has 50-249 employees, 2015-2017 (1=Yes, 0=Otherwise)	3,587	0.17	0.37
AGE05	Age of business between 0 - 5 years, 2015-2017 (1=Yes, 0=Otherwise)	3,294	0.08	0.28
SOLE TRADER	Whether a firm is sole proprietorship, 2015-2017 (1=Yes, 0=Otherwise)	3587	0.13	0.33
CAPABILITY FINANCE	Whether a firm has a well-developed capability for external finance, 2015 (1=Strong capability, 0=Otherwise)	2,656	0.48	0.50
CAPABILITY STRATEGY	Whether a firm has a well-developed capability for developing and implementing a business plan and strategy, 2015. (1=Strong capability, 0=Otherwise)	3,526	0.64	0.48
CAPABILITY OPERATION	Whether a firm has a well-developed capability for operational management, 2015. (1=Strong capability, 0=Otherwise)	3,459	0.71	0.45
CAPABILITY INNOVATION	Whether a firm has a well-developed capability for developing and introducing new products or services, 2015. (1=Strong capability, 0=Otherwise)	3,284	0.60	0.49
WOMEN-LED BUSINESS	Whether a firm is a women-led business, 2015-2017 (1=Yes, 0=Otherwise)	3,587	0.21	0.41
PRIMARY	Whether a firm operates in the primary sector, 2015-2017 (1=Yes, 0=Otherwise)	3,587	0.04	0.29
MANUFACTURING	Whether a firm operates in the manufacturing sector, 2015-2017 (1=Yes, 0=Otherwise)	3,587	0.09	0.29
CONSTRUCTION	Whether a firm operates in the construction sector, 2015-2017 (1=Yes, 0=Otherwise)	3,587	0.08	0.27
WHOLESALE RETAIL	Whether a firm operates in the wholesale/retail sector, 2015-2017 (1=Yes, 0=Otherwise)	3,587	0.14	0.34
TRANSPORT	Whether a firm operates in the transport/storage sector, 2015-2017 (1=Yes, 0=Otherwise)	3,587	0.03	0.17

Variable	Definition	Obs.	Mean	S.D.
ACCOMODATION	Whether a firm operates in the accommodation/food sector, 201-2017 (1=Yes, 0=Otherwise)	3,587	0.06	0.23
INFORMATION	Whether a firm operates in the information/communication sector, 2015-2017 (1=Yes, 0=Otherwise)	3,587	0.06	0.24
FINANCE	Whether a firm operates in the financial/real estate sector, 2015-2017 (1=Yes, 0=Otherwise)	3,587	0.04	0.20
PROFESSIONAL	Whether a firm operates in the professional/scientific sector, 2015-2017 (1=Yes, 0=Otherwise)	3,587	0.18	0.39
ADMINISTRATION	Whether a firm operates in the administrative/support sector, 2015-2017 (1=Yes, 0=Otherwise)	3,587	0.07	0.25
EDUCATION	Whether a firm operates in the education sector, 2015-2017 (1=Yes, 0=Otherwise)	3,587	0.05	0.21
HEALTH	Whether a firm operates in the health/social work sector, 2015-2017 (1=Yes, 0=Otherwise)	3,587	0.10	0.29
ARTS	Whether a firm operates in the arts/entertainment sector, 2015-2017 (1=Yes, 0=Otherwise)	3,587	0.03	0.17
OWN WEB	Whether a firm has its own website, 2015 (1=Yes, 0=Otherwise)	3,587	0.82	0.38
THIRD-PARTY WEB	Whether a firm uses a third party website to promote or sell, 2015 (1=Yes, 0=Otherwise)	3,587	0.18	0.38
LSE	Businesses located in London and South East, 2015-2017 (1=Yes, 0=Otherwise)	3,534	0.20	0.40
SUPPORT	Whether a firm has received information or advice in last 12 months, 2015-2017 (1=Yes, 0=Otherwise)	3,586	0.36	0.48
MEDIA	Whether a firm is being a member of a social media business network, 2015 (England) (1=Yes, 0=Otherwise)	3,587	0.54	0.50
CHAMBER	Whether a firm is being a member of Local Chamber of Commerce, 2015 (England) (1=Yes, 0=Otherwise)	3,587	0.22	0.41
LEP-level				
BROADBAND	Average number of businesses who are unable to access broadband speed as least 2M/bit in each LEP (%), 2015-2017 (discrete)	3,534	0.45	0.54
NVQ4	The percentage of population who have the National Vocational Qualification Level 4 or above in each LEP (16-64 year olds), 2015-2017 (discrete)	3,534	37.50	7.44

Table 3 - Determinants of SMEs' productivity in England

	One-level GLS	**Two-level mixed effects**				
Firm productivity	**Model 0**	**Model I**	**Model II**	**Model III**	**Model IV**	**Model V**
rural	0.0171		0.0789**	0.0623**	0.0112	0.0129
	(0.34)		(2.48)	(1.98)	(0.26)	(0.30)
support	0.0158		0.0690**	0.0634**	0.0624**	0.0625**
	(0.79)		(2.49)	(2.31)	(2.27)	(2.28)
family	-0.0235		-0.0252	-0.0253	-0.0254	-0.0245
	(-0.67)		(-0.83)	(-0.83)	(-0.84)	(-0.81)
age≤ 5years	0.00597		-0.0853*	-0.0739	-0.0727	-0.0731
	(0.12)		(-1.88)	(-1.64)	(-1.62)	(-1.63)
sole trader	-0.352***		-0.302***	-0.301***	-0.301***	-0.303***
	(-5.60)		(-6.98)	(-7.02)	(-7.02)	(-7.06)
micro	-0.199***		-0.0618*	-0.0589*	-0.0603*	-0.0604*
	(-7.02)		(-1.77)	(-1.71)	(-1.75)	(-1.75)
small	-0.0538		0.153***	0.141***	0.141***	0.140***
	(-1.39)		(3.97)	(3.72)	(3.72)	(3.70)
medium	-0.164***		0.136***	0.131***	0.131***	0.133***
	(-3.48)		(2.87)	(2.80)	(2.80)	(2.85)
primary	0.724***		0.765***	0.777***	0.773***	0.772***
	(4.79)		(7.62)	(7.86)	(7.83)	(7.82)
manufacturing	0.983***		0.980***	0.986***	0.983***	0.983***
	(8.41)		(12.69)	(12.98)	(12.94)	(12.95)
construction	0.837***		0.914***	0.915***	0.913***	0.912***
	(6.93)		(11.46)	(11.67)	(11.65)	(11.65)
wholesale & retail	1.229***		1.270***	1.358***	1.358***	1.362***
	(10.85)		(16.96)	(14.05)	(13.99)	(13.97)
transport	0.422***		0.499***	0.509***	0.506***	0.503***
	(2.76)		(4.88)	(5.06)	(5.03)	(5.00)
accommodation	0.148		0.167*	0.170**	0.170**	0.170**
	(1.11)		(1.91)	(1.97)	(1.98)	(1.97)
information	0.514***		0.539***	0.532***	0.530***	0.530***
	(3.96)		(6.29)	(6.32)	(6.31)	(6.30)
financial	0.965***		1.006***	0.943***	0.941***	0.946***
	(7.01)		(11.06)	(5.34)	(5.37)	(5.39)
professional	0.412***		0.498***	0.494***	0.492***	0.490***
	(3.74)		(6.84)	(6.90)	(6.88)	(6.85)
admin	0.291**		0.365***	0.367***	0.363***	0.361***
	(2.34)		(4.43)	(4.53)	(4.49)	(4.45)
education	-0.0120		0.0163	0.0219	0.0205	0.0196
	(-0.09)		(0.18)	(0.24)	(0.23)	(0.22)
health	-0.519***		-0.466***	-0.458***	-0.462***	-0.464***
	(-4.43)		(-5.91)	(-5.91)	(-5.95)	(-5.99)
arts	-0.0971		0.0130	0.0180	0.0152	0.0126
	(-0.64)		(0.13)	(0.18)	(0.15)	(0.13)
capability operation	0.0459		0.0316	0.0313	0.0320	0.0333
	(1.00)		(1.08)	(1.08)	(1.10)	(1.15)
capability finance	0.132***		0.118***	0.0950***	0.0940***	0.0939***
	(3.12)		(4.31)	(3.49)	(3.46)	(3.45)

(continued)	Model 0	Model I	Model II	Model III	Model IV	Model V
capability innovation	-0.0458 (-1.06)		-0.0377 (-1.36)	-0.0292 (-1.06)	-0.0304 (-1.11)	-0.0309 (-1.13)
capability strategy	0.130*** (2.89)		0.104*** (3.58)	0.110*** (3.80)	0.111*** (3.85)	0.112*** (3.88)
media network	0.0231 (0.53)		0.0340 (1.21)	0.0485* (1.73)	0.0486* (1.74)	0.0476* (1.70)
Chamber network	0.106** (2.11)		0.0524 (1.60)	0.0547* (1.67)	0.0552* (1.69)	0.0543* (1.66)
women-led business	-0.155*** (-3.66)		-0.258*** (-7.42)	-0.258*** (-7.48)	-0.257*** (-7.47)	-0.257*** (-7.45)
own website	0.188*** (3.15)		0.151*** (3.94)	0.132*** (3.46)	0.132*** (3.46)	0.133*** (3.48)
third party website	-0.0708 (-1.36)		-0.0409 (-1.21)	-0.0508 (-1.51)	-0.0516 (-1.54)	-0.0525 (-1.56)
broadband	-0.0432 (-1.51)		-0.0469 (-1.46)	-0.0403 (-1.28)	-0.0803** (-2.10)	-0.0725* (-1.92)
education nvq4	0.00848*** (2.98)		0.0103*** (3.28)	0.00971*** (3.23)	0.00980*** (3.37)	0.00848*** (3.08)
year 2016	0.0950*** (5.23)		0.0929*** (2.85)	0.0949*** (2.96)	0.0943*** (2.94)	0.0967*** (3.02)
year 2017	0.0857*** (4.83)		0.102*** (3.20)	0.103*** (3.29)	0.102*** (3.27)	0.105*** (3.35)
rural*broadband	0.0554 (1.37)				0.0896* (1.73)	0.0892* (1.73)
LSE	0.124** (2.26)					0.122** (2.11)
constant	9.614*** (60.34)	10.634*** (444.20)	9.420*** (65.43)	9.452*** (67.51)	9.468*** (68.68)	9.496*** (72.18)
RE Var at LEP						
Random intercept	-	0.015***	0.008***	0.006***	0.005*	0.003
Financial sector	-	-	-	0.616***	0.604***	0.653***
Wholesale-Retail	-	-	-	0.120***	0.122***	0.125***
IntraClass Cor. ICC	-	1.14%	0.80%	0.64%	0.55%	0.32%
LR Test (one-level)	-	89.09***	15.71***	134.94***	132.66***	131.23***
LR Test (model II)	-	-	-	119.22***	122.14***	125.93***
Nr. observations	5,831	9591	5,831	5,831	5,831	5,831
Nr. of groups	-	38	38	38	38	38
Observations per group min-max	-	69 - 1,186	15 - 714	15 - 714	15 - 714	15 - 714

z-score statistics in parentheses. *, **, *** denote significance at 10%, 5% and 1% level respectively. RE is random effects. Var is variance.
Model 0 is fitted with a Generalised Linear Regression estimator (i.e. random effects). Models I-V are fitted with a 2-level Mixed Effects estimator.
Model I is an empty regression (no control variables) with a random intercept at LEP level, in addition to a fixed intercept estimated across all observations. Model II introduces all firm-level variables and the two LEP-level variables listed in Table 2, plus time dummies and fixed intercept, which together enter the fixed-effect part of the model, in addition to a random intercept at LEP-level. Model III augments Model II with the inclusion of two random slopes estimated with RE at LEP level for the Financial sector and Wholesale -Retail sector dummies. Model IV augments model III with the inclusion of the interaction variable rural-broadband. Model V augments the fixed-effects part of model IV with the inclusion of the LSE dummy.
LR test results (one-level) are obtained comparing all models with one-level linear regression
LR test (model II) results are obtained comparing models III-V with model II.

Centre Manager
Enterprise Research Centre
Warwick Business School
Coventry, CV4 7AL
CentreManager@enterpriseresearch.ac.uk

Centre Manager
Enterprise Research Centre
Aston Business School
Birmingham B4 7ET
CentreManager@enterpriseresearch.ac.uk