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Rural businesses and levelling up: A rural-urban analysis of business innovation and exporting in England's north and midlands

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ABSTRACT

In the face of persistent and widening regional imbalances in economic and social outcomes, the UK Government seeks to 'level up' less prosperous communities, reigniting debates on the relationships between geography and business innovation. A key question concerns whether cities provide a more favourable environment for business innovation and exporting. However, the comparative performance of urban and rural Small and Medium Sized Enterprises (SMEs) within less prosperous regions has received little attention. Using Longitudinal Small Business Survey data, we apply Propensity Score Matching to study urban-rural differences in SME performance in the North and Midlands of England. The findings reveal no systematic, significant differences in goods, service and process innovation or exporting between rural and urban SMEs, suggesting that the emphasis on urban focused growth in the levelling up agenda appears misplaced.

1. Introduction

Regional variations in economic and social outcomes are sizable and enduring across developed economies (OECD, 2016), with lagging regions typically falling further behind (McCann and Yuan, 2022; OECD, 2019). Moreover, the COVID-19 pandemic served to further exacerbate and expose regional disparities (Bhattacharjee et al., 2020) as well as the urgency of finding remedies to this longstanding challenge (Westwood et al., 2022). Where residents feel 'left behind' political backlashes against globalisation and open trading relationships have occurred (Urbanska and Guimond, 2018). These problems are unlikely to disappear soon as economically lagging regions appear more vulnerable to automation, the adverse effects of ageing populations, trade disruption, and health risks (Bhattacharjee et al., 2020; McCann, 2020; McCann and Yuan, 2022; OECD, 2018). In addressing this problem, Small and Medium Sized Enterprises (SMEs) are of central importance. Across developed economies, SMEs account for approximately 70 per cent of jobs and generate between 50 and 60 per cent of value added, and are integral to improving the fortunes of lagging regions, contributing to employment, innovation and productivity growth (Freshwater et al., 2019; OECD, 2017).

In the UK, disparities are particularly marked and growing, resulting from the imbalance between London and the rest of the South East of England and other regions, and there are also significant disparities within regions (HM Government, 2022; McCann and Yuan, 2022). For instance, London's Gross Value Added (GVA) per head rose from 167% of the UK average in 1998 to 181% in 2020 (ONS, 2022). In contrast, most of the North and Midlands lost ground - between 1998 and 2020 GVA per head as a percentage of the UK average fell across the regions of the North East (75%–71%), Yorkshire and Humber (84%–79%), East Midlands (87%–80%) and West Midlands (89%–81%) (ONS, 2022). Only the North West recorded a modest improvement during this time period, from 86% to 88% of the UK average (ONS, 2022). Mirroring variations in GVA, the number of small businesses per head of the population, as well as rates of R&D expenditure and patent registration have been consistently lower in the Midlands and the North, compared with London and the rest of the South East of England (Intellectual Property Office, 2019; KPMG, 2017).

The UK Government seeks to address these spatial disparities through its flagship policy of levelling up (HM Government, 2022). While acknowledging a complex pattern of spatial disparities in incomes and living standards, with some pockets of high deprivation in the south

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of England, most of the focus of the levelling up agenda, both economically and politically, is on England's north and midlands (HM Government, 2022; Tomaney and Pike, 2020). The north of England consists of the former Government Office Regions of the North East, North West, and Yorkshire and Humber, collectively labelled the 'Northern Powerhouse' (NP) (HM Government, 2016). The Midlands consists of the former Government Office Regions for the West Midlands and East Midlands, which was branded in 2016 the 'Midlands Engine' (ME) (Midlands Engine, 2017). The analysis in this paper focuses on the NP and ME territories.

The Levelling Up White Paper presents a framework to identify the drivers of disparity, arguing that they stem from spatial variations in the endowments of six types of capital – physical, human, intangible, financial, social, and institutional (HM Government, 2022). Accordingly, business dynamism, measured in terms of innovation, growth and international trade varies across localities as endowments of the six types of capital and their ability to be combined differ spatially (HM Government, 2022). This raises the question as to what type of locality may be most amenable to fostering capital accumulation and combination. On this the White Paper identifies cities as offering a preferable location, arguing that the close co-location of people, business and finance can generate positive spill-overs, or agglomeration effects which boost business dynamism (HM Government, 2022). Consequently, urban areas 'play fundamental roles as engines of growth' (HM Government, 2022, p.33), with Europe having a long history of 'city-centric growth' (HM Government, 2022, p.3).

While on one hand the White Paper argues that cities provide a more favourable environment for enterprise on which to build Levelling Up strategies, it also acknowledges that for 'levelling up to mean something to people in their daily lives, we need to reach into every community in the country, from city centres to rural areas' (HM Government, 2022, p. xxiv). Moreover, it aspires 'for every place in the UK to have a rich endowment of all six capitals, so that people do not have to leave their community to live a good life' (HM Government, 2022, p. xvi).

This all begs the question as to how rural businesses, in less prosperous regions, perform in relation to their urban counterparts and, in turn, whether the city emphasis of the Levelling Up agenda is warranted. The White Paper itself, and the run up to its publication, stimulated considerable critique from rural stakeholders, concerned with the lack of attention to the challenges and contributions of rural areas and the granularity of analysis, which masks rural issues (Pragmatix Advisory, 2022; Rural Services Network, 2022; Turner et al., 2021). However, empirical evidence on this question remains limited, with the White Paper itself noting substantial gaps in subnational and local analysis. Specifically, there is a lack of research distinguishing whether any urban-rural variations in innovation and exporting in the NP and ME regions exist, and if they do whether they stem from a stock of small businesses with particular profile characteristics (by sector, age, size etc.) or if after controlling for such factors, any variations in performance persist (i.e., a rural or urban location effect).

This paper therefore undertakes a rural-urban comparative analysis of SME performance, measured in terms of innovation and exporting in the NP and ME regions. By doing this, our study makes three contributions to knowledge. Firstly, we critically assess the ability of rural and urban areas to stimulate business innovation and exporting, as a central question underpinning debates regarding the geographical focus of levelling up. Secondly, the study is empirically novel in that it examines the differences in innovation and export performance between SMEs in the NP and ME regions using a large cross-sectional dataset. To do this, we apply Propensity Score Matching (PSM) which is effective in addressing selection bias in observational studies when comparing between two study groups, providing a more precise assessment of any "rural effect" on innovation and export performance. Finally, based on the analysis, the paper contributes to current policy debates on levelling up, regarding the relative merits of urban and rural locations in fostering business dynamism within less prosperous regions. Specifically, the analysis unpacks the relationship between rural locations and product/process innovation and goods/service/potential export performance, as well as distinguishing between new-to-the-market and new-to-the-business innovation. The paper thus expands the evidence base in ways relevant to both academics and policy makers concerned with rural development.

We begin by documenting the arguments, informed by agglomeration theory, that cities may be better placed to foster business innovation and exporting than rural areas. A description of the data and statistical methods employed for analysing the comparative performance of rural and urban SMEs follows. The results section presents the PSM estimations, followed by a discussion of the results, discussing why arguments based on agglomeration theory appear overstated in less prosperous regions, contributing to the literatures on spatial variations in business innovation and propensity to export. The final section considers opportunities for future research.

2. Agglomeration theory and urban-rural variations in business innovation and exporting

Agglomeration theory, drawing on notions of actor and institutional density, suggests that urban locations are best placed to foster business innovation in less prosperous regions (Fujita et al., 2001; Puga, 2010). Specifically, the co-location and close physical proximity of people, business and finance generate positive spill-overs (agglomeration effects) which foster business dynamism.

Duranton and Puga (2001) introduce a formal model to explain the superiority of urban environments for stimulating business innovation. They argue that firms need to experiment to realise their full potential, with optimal production processes emerging from trial and error. Firms therefore produce multiple "prototypes" in the search for an ideal production process and products, or, in other words, a sustainable business model. The production of prototypes incurs costs, namely of physical inputs and labour, with each prototype requiring differing inputs and workers with varying skill sets. For this process of innovation, Duranton and Puga (2001) argue that cities are better positioned to act as nurseries due to agglomeration economies, characterised as matching, sharing, and learning (Duranton and Puga, 2004).

Matching refers to hiring labour, with urban areas offering a larger and more diverse set of potential workers (Puga, 2010). A larger and more diverse labour pool improves the expected quality of each match and reduces employers' search costs (Duranton and Puga, 2004). In contrast, rural areas suffer from thinner labour markets, particularly for skilled graduates, which empirical evidence suggests hinder firms' ability to compete in knowledge-based economies and innovate (Evers, 2019; Tödtling and Trippl, 2005).

Sharing refers to indivisibilities in the provision of particular goods or facilities, with cities facilitating the sharing of indivisible public goods, production facilities, and marketplaces (Duranton and Puga, 2004). Rural areas, however, typically lack sufficient businesses and residents to support indivisible facilities such as business support agencies and universities. Empirical evidence suggests such institutions are key enablers of innovation (Kalcheva et al., 2018). Given the lack of a critical mass of actors in rural areas, with which to share costs, universities and business support agencies are typically urban based and their reach into rural areas is, at best, patchy (Hindle et al., 2010; Smallbone et al., 2003). Due to their dispersed nature and greater travel distances, the cost of providing support services to rural businesses is greater than comparable urban provision (Hindle et al., 2010; Smallbone et al., 2003). To meet their own targets for engagement and revenue generation, agencies supporting business innovation consequently may focus their activities on urban areas. Empirical evidence also suggests that rural firms have weaker access to public research (Hindle et al., 2010) and specialist external finance, such as private venture capital (Florida and King, 2018).

Learning encompasses both tacit and codified knowledge (Hamidi et al., 2019). Learning depends on interactions between relevant actors and in-person contact is typically seen as superior for generating information and skill spill-overs (Glückler, 2007), especially relating to tacit knowledge (Ray et al., 2020). Agglomeration models assume that physical proximity to individuals with superior knowledge and skills facilitates the acquisition of skills by others as well as the exchange and diffusion of knowledge (Duranton and Puga, 2004). Consequently, the generation and transmission of knowledge is 'sticky' in space (Huggins and Thompson, 2014). Urban areas, through greater population density and physical proximity are predicted to facilitating learning to a greater extent than rural areas (Duranton and Puga, 2004), aiding business innovation, particularly in knowledge-based sectors and the creative industries (Florida, 2014). Supporting empirical evidence indicates that rural firms, especially those in very remote and low population density localities, are less likely to register patents and trademarks (Roper, 2020) or engage in new to the market innovation (Phillipson et al., 2019).

Based on models of agglomeration and the importance of matching, sharing, and learning for innovation, we therefore test Hypothesis 1: *rural areas provide a less favourable environment for business innovation, so that rural SMEs are less likely to realise (a) product innovation and (b) process innovation than their urban counterparts.*

Models of agglomeration economies assume that the advantages of urban areas (e.g., matching, sharing, and learning) which facilitate business innovation also aid exporting (Greenaway and Kneller, 2008). This assumption recognises that exporting may require employees with different skillsets from those already employed within a firm, such as foreign language fluency and market knowledge, with urban areas more likely to generate satisfactory worker-skill matches because of larger and more diverse labour markets (Freeman et al., 2012). Regarding sharing, firms in urban areas have better access to specialised infrastructures that aid internationalisation, such as export advisers, support services and agents (Freeman and Styles, 2014; Freeman et al., 2012).

Regarding learning, urban areas may generate higher network capital amongst businesses (Huggins et al., 2018) which is vital to exporting as the latter depends on flows of knowledge between agents capable of exploiting international market opportunities (Huggins and Thompson, 2014, 2015). In contrast, as the density of other businesses and their owners is lower than in cities, rural businesses may possess lower network capital, hampering the understanding of international market opportunities (Lee and Rodríguez-Pose, 2013) as well as access to reputation networks and referrals (Glückler, 2007). Lower levels of network capital may be exacerbated by weaker institutional linkages, such as to business support and export development agencies (Huggins and Thompson, 2014). Supporting empirical research suggests access to export-related infrastructure and networking opportunities positively affect strategic export performance (Freeman and Styles, 2014). Consequently, our paper also tests Hypothesis 2 that: *rural areas provide a less favourable environment for stimulating exports, so that rural SMEs are less likely to realise exports of (a) goods and (b) services than their urban counterparts*.

3. Data and methodology

3.1. Data

The analysis draws on data from the UK's Longitudinal Small Business Survey (LSBS) commissioned by the Department for Business, Energy, and Industrial Strategy (BEIS). A small business survey for businesses with fewer than 250 employees has been conducted annually in the UK since 2003, but only since 2015 has the survey incorporated a longitudinal component and been known as the LSBS (BEIS, 2019). It is a large-scale telephone survey of SME owners and managers across the UK, based on a random sample of registered and unregistered businesses taken from the Inter-Departmental Business Register (IDBR) and Dun & Bradstreet records, respectively. The sample is stratified by each UK nation. The survey contains data on firm characteristics, such as firm size, sector, number of employees, and ownership structure. It also includes information on each business' recent performance, obstacles, plans and expectations. We utilise cross-sectional data for the first year of the LSBS (2015) and for 2018, the most recent year for which data were available to researchers at the time of the analysis. Due to the high rate of churn in LSBS participants, generating a relatively small number of observations in both the 2015 and 2018 datasets, reflecting high small business birth and death rates more widely, it was not possible to analyse as panel data.

Table 1 presents the number of SMEs in both the NP and ME samples. We allocated enterprises to the NP and ME locations using the Local Enterprise Partnership (LEP) classification in the dataset. The analysis excludes farms to remove the influence of such land-based businesses which operate in a very different policy environment from non-farm enterprises. In 2015, data from 15,501 SMEs were collected across the UK, of which 17.9% (2776) were in the NP region and 16.4% (2542) were located in the ME region. In 2018, the total number of SMEs included in the LSBS was 15,015 of which 18.4% (2757) and 17.1% (2568) were in the NP and ME regions respectively. Based on their postcode and the official ONS definition, businesses were classified as either rural or urban (ONS, 2013). In the NP region, approximately 20% (549) and 22% (594) were located in rural areas in 2015 and 2018, respectively. While 29% (731) and 29% (747) were located in rural areas in 2015 and 2018 in the ME region.

We applied BEIS's weightings to address imbalances in sampling from IDBR and Dun & Bradstreet records so that the data represents the overall SME population in each year. Specifically, the responses for LSBS 2015 and 2018 were weighted according to BEIS Business Population Estimates (BPE) by legal status, business size, sector, and nation for each year. In practice, the application of weightings makes the smallest sampled businesses relatively more important to reflect the actual distribution of businesses in the population. This reflects how, to ensure that there are sufficient medium sized businesses in the LSBS to draw meaningful conclusions about this cohort, they are oversampled according to their importance in the business population. The BPE provides information on the structure of the UK's business population at both regional and national levels.

3.2. Independent variables

Table 2 details the independent and dependent variables used in the analysis for the NP and ME areas, as well as for the UK overall. For independent variables the paper focuses on the profile characteristics of businesses, which constitute internal factors that determine enterprise performance. Specifically, the analysis considers size, sector, and age of the business as well as if the business is women-owned, family owned or a sole trader. We include business sector in the models to control for sectoral heterogeneity in rural and urban SMEs. Following Phillipson et al. (2019), we classify enterprises according to four broad sectors, namely: 1) primary, production and construction, 2) transport, retail and food service, 3) business services, and 4) other services (used as the default). In addition, business size can influence the capacity of rural and urban SMEs to improve their business performance (Heimonen, 2012). Thus, to control for business size, we include this variable in the model with three dummies for micro, small and medium businesses,

Table 1
LSBS sample of SMEs in each location and region.

Region	2015		Total	2018		Total
	Rural	Urban		Rural	Urban	
Northern Powerhouse (NP)	549	2227	2776	594	2163	2757
Midlands Engine (ME)	731	1811	2542	747	1821	2568

Note: We exclude farms from the analysis.
Source: analysis based on LSBS (2015, 2018).

Table 2
Definition of the Variables and descriptive statistics for Northern Powerhouse and Midlands Engine based SMEs.

Variable	Definition	Northern Powerhouse (NP)				Midlands Engine (ME)				UK			
		2015		2018		2015		2018		2015		2018	
		Rural	Urban	Rural	Urban	Rural	Urban	Rural	Urban	Rural	Urban	Rural	Urban
Explanatory PROCN[a]	= 1 if in production and construction sectors; 0 = otherwise	23.8%**	26.5%**	31.1%**	22.6%**	23.5%**	24.8%**	24.6%**	25.3%**	25.1%**	23.8%**	27.5%**	22.6%**
TRANST	= 1 if operate in transport, retail and food service sectors; 0 = otherwise	26.6%**	17.9%**	25.6%**	20.4%**	18.5%**	18.4%**	18.6%**	19.6%**	23.0%**	17.1%**	22.9%**	17.9%**
SERVICE	= 1 if operate in business service sector; 0 = otherwise	23.9%**	30.7%**	25.9%**	30.8%**	36.0%**	30.3%**	37.1%**	28.3%**	31.4%**	34.5%**	34.6%**	32.2%**
MICRO	= 1 if 1–9 employees; 0 = otherwise	16.5%	17.7%	22.1%	19.9%	22.2%	19.2%	21.5%	17.7%	21.5%**	18.8%**	20.9%**	19.4%**
SMALL	= 1 if 10–49 employees; 0 = otherwise	3.4%	3.7%	3.6%	4.0%	4.4%	3.8%	3.0%	3.6%	3.7%**	3.9%**	3.4%**	3.9%**
MEDIUM	= 1 if 50–249 employees; 0 = otherwise	0.7%	0.5%	0.5%	0.7%	0.6%	0.7%	0.4%	0.7%	0.5%**	0.6%**	0.4%**	0.7%**
SOTRAD	= 1 if sole trader; 0 = otherwise	50.6%**	55.6%**	47.0%	45.7%	48.4%	52.7%	43.8%**	46.3%**	48.9%**	50.8%**	46.4%**	44.0%**
FAMILY	= 1 if owned by family; 0 = otherwise	85.3%	86.9%	90.2%	87.1%	86.4%	84.6%	92.2%**	85.7%**	86.2%	85.0%	90.0%**	86.2%**
WOMEN	= 1 if women-led businesses; 0 = otherwise	16.9%	20.7%	19.4%	20.6%	24.6%	22.3%	21.3%	20.0%	20.6%	19.4%	20.6%	21.7%
AGE05	= 1 if age between 0 and 5 years	8.4%**	17.3%**	16.1%**	26.1%**	12.6%**	16.4%**	18.7%**	25.3%**	12.2%**	16.6%**	16.6%**	24.5%**
AGE20	= 1 if age more than 20 years	44.4%**	37.6%**	33.2%**	28.3%**	39.3%**	32.5%**	37.1%**	31.1%**	43.5%**	40.3%**	35.8%**	30.7%**
Outcome													
EXGOOD	Whether export goods (1 = Yes; 0 = otherwise)	3.6%	4.5%	7.0%**	4.8%**	6.9%**	4.9%**	7.9%	6.3%	6.7%**	5.0%**	7.5%**	6.1%**
EXSERV	Whether export services (1 = Yes; 0 = otherwise)	5.4%	5.3%	5.9%	6.7%	10.2%**	5.6%**	9.6%**	7.4%**	8.5%	8.4%	9.1%	9.6%
PROTEX	Whether have goods/services that are suitable to export (but have not exported yet) (1 = Yes; 0 = otherwise)	16.4%**	14.8%**	17.5%	16.9%	17.1%	15.7%	21.8%**	13.9%**	16.8%	16.4%	19.1%	17.3%
GDINNO	Product innovation - whether have new or significantly improved goods/ services in last 3 years (1 = Yes; 0 = otherwise)	31.4%	34.1%	14.4%**	17.9%**	43.4%**	37.4%**	19.6%	18.7%	38.1%**	36.2%**	19.6%	19.1%
PRINNO	Process innovation - whether SMEs have new or significantly improved processes in the last 3 years (1 = Yes; 0 = otherwise)	16.9%	16.8%	18.4%**	15.3%**	16.1%	17.2%	12.1%**	15.1%**	18.9%	18.3%	15.5%	15.1%
Treatment RURAL	= 1 if located in rural area; 0 = otherwise												

Note: Weighed percentages are reported, with ** indicating that the difference is statistically significant (χ^2: $p < 0.05$).
[a] We exclude farms from the analysis.

leaving as the default businesses without employees. We also control for the effect of gender on business performance between rural and urban enterprises. This follows Carter et al. (2015) who report that women-led businesses overall register relatively weaker performance, and Rose (2019) who found that business networking and mentorship is less accessible to women entrepreneurs living in rural areas. Moreover, we include whether the business is family owned, since such enterprises are more likely to have non-financial objectives that affect performance (Howorth and Robinson, 2021; Westhead and Cowling, 1997) and represent a higher proportion of the business population in rural areas (Phillipson et al., 2019). The analysis also includes sole proprietorship to control for this type of business ownership, since Abdo Ahmad and Fakih (2022) found that such firms have competitive disadvantages against those with open and closed shareholders as well as partnerships and limited partnership arrangements. Finally, we include age of business, as an important firm-specific factor that influences business performance, reflecting how age is related to business reputation, skills and experience (Rosenbusch et al., 2011). Specifically, age is controlled for with two dummies, namely one dummy capturing young businesses up to five years old, and one dummy capturing businesses that have been trading for more than twenty years, leaving those businesses aged between 6 and 20 years as the default.

Table 2 reports Chi-square (χ^2) statistics considering urban-rural differences for the independent variables, with significant differences identified. This reveals that, for example, more urban than rural SMEs were in the service sector in the NP region in 2015 and 2018. Moreover, more young businesses aged 0–5 years were present in urban areas in both the NP and ME regions in both 2015 and 2018. An inconsistent pattern is apparent in the data between the reference years in relation to the proportion of businesses aged more than twenty years in the NP region, since in 2015 there are more older businesses in rural areas, but in 2018 there were relatively more older businesses in urban areas. These differences may reflect the high degree of churn in sampled enterprises (BEIS, 2019).

3.3. Dependent variables

Regarding dependent variables we consider two dimensions of SME performance: exporting and innovation. Regarding exporting, in the LSBS 2015 and 2018 firms reported whether they had exported goods or services in the previous 12 months. If businesses had not been involved in exporting activities, the LSBS asked whether they had goods and services that were suitable for export, referred to as potential exports. For innovation, firms reported whether they had new or significantly improved goods/services (product innovation) as well as processes (process innovation) in the previous three years. In addition, the data distinguishes between innovation that is new to the world, from that which is merely new to the business.

3.4. Propensity Score Matching (PSM)

In the analysis we are also interested in considering whether the performance of a rural business in the ME or NP territories would be substantially different if the same business had been located in an urban area rather than a rural one. This question is difficult to address through observations, as only very few businesses change location (and that would mean that they do not exist simultaneously in two locations anyway, introducing a time lag in the comparison of their performance). Consequently, we face the task of building a counterfactual for what we cannot observe. Building what can be called a locational counterfactual means identifying for each rural business in our sample another urban business, or a set of them, with very similar characteristics. To control for key business profile characteristics in comparing business performance between rural and urban SMEs, and more precisely assess rural and urban effects, we thus undertook exact matched-pair comparisons of rural and urban enterprises located in the NP and ME regions. For this, we employed Propensity Score Matching (PSM) techniques (Rosenbaum and Rubin, 1983) which are widely used to estimate causal effects in observational studies. In this analysis, there are two groups of businesses, the treated (rural SMEs) and untreated (urban SMEs). In the same way that the classification of treated/untreated units in quasi-experimental methods is the result of a human behaviour (say smoking), here where to locate the business (our treatment) is the result of a choice by the entrepreneur, and the PSM conveniently allows us to build locational counterfactuals for rural businesses and match them with urban ones with similar characteristics. PSM is thus a method to reduce estimation bias and improve accuracy when units are not randomly assigned to treatments, like in this case, as the researchers cannot randomly assign a location to existing businesses. Moreover, having more units in the control group than the treatment group, as in our sample there are far more urban businesses than rural ones, allows for better predictions (Stuart et al., 2011).

The matching process involves balancing many observed characteristics (covariates) between the two groups by compressing the variables into a single score. This permits a comparison of the performance of individual SMEs with similar (matched) propensity scores across the treated and control/untreated groups. The propensity score, defined as the conditional probability of assigning a business to a rural location when the observed covariates are considered, is estimated using a logit model which takes the form:

$$PS(X_{ijt}) = Pr(D_{ijt} = 1 | \mathbf{X}_{ijt}) = \beta_0 + \beta_1 \mathbf{X}_{ijt} \tag{1}$$

where $PS(X_i)$ is propensity score of ith firm, $Pr\ (D_i = 1)$ is the probability of ith firm being in the rural areas (treated group): $D = 1$ when firms are located in rural areas, i is the number of firms; $i = 1, \ldots, n$, j represents a region, with values $j = 1$ for the NP area and $j = 2$ for the ME area; t represents years, with values $t = 1$ for 2015 and $t = 2$ for 2018; $\mathbf{X}$ is a vector of observed variables that should be controlled for before comparing the outcomes such as business size, firm age, sector, and family firm status (see Table 2).

Based on the propensity score, the matching process is conducted, which can utilise various approaches such as nearest-neighbour matching or caliper matching (Guo and Fraser, 2010). To assess the consistency of the PSM results we undertook three different matching approaches, namely the nearest neighbour (1–1) PSM, the three-nearest neighbours (3–1) and the caliper, employing the command *teffects psmatch* in Stata. The first matching method is the default, whereby the Average Treatment Effect for the Treated (ATET) is estimated by matching each rural business to a single urban business whose propensity score is the closest. The second matching method uses a weighted average of the three nearest urban businesses to a rural business in terms of similarity of propensity scores, which improves the efficiency of the estimator for ATET but also increases the finite sample bias because of the potential danger of matching dissimilar observations. The caliper sets the maximum distance (measured as the absolute difference in the estimated propensity scores) for matches: the lower the distance allowed, the higher the similarity of the observations matched, but it is also less likely to find a match at all. In addition, in assessing matching quality, a balancing test[1] should be satisfied to ensure that there are no significant differences on covariate means between the treatment and control groups (Dehejia and Wahba, 2002). If balancing tests are passed, the Average Treatment Effect for the Treated (ATET) on business performance between rural and urban SMEs is then calculated:

$$ATET = E[Y_{1ijt} - Y_{0ijt} \mid D_{ijt} = 1] \tag{2}$$

where Y_{1ij} and Y_{0ij} represent the business performance for ith firm being located in rural and urban areas in jth region during tth year,

[1] Results available in supplementary files.

respectively. Here, we measure business performance in terms of innovation and exporting as previously discussed.

Given the objectives of the study, PSM is preferred to more conventional probit or logit regression models for several reasons. PSM efficiently collapses a range of covariates into a score and therefore avoids the "dimensionality problem" that occurs when units in the treatment and control groups are balanced on many covariates one at a time (Guo and Fraser, 2010). Secondly, previous assessments suggest that PSM is more robust and precise and has greater power than logistic regression (Rubin, 2007) and is an effective technique to reduce selection bias (Cepeda et al., 2003). Finally, PSM is a two-step approach which allows us to control for variations in business characteristics and to identify key characteristics of the treatment group (rural location), before comparing the outcomes.

4. Findings: comparing rural and urban SME performance

In Table 2, we report differences in business performance between rural and urban SMEs for 2015 and 2018. At this stage, we provide an overview of differences between the stock of rural and urban SMEs as a whole for the outcome variables before controlling for selection bias and variations in business characteristics.

For exporting, in the NP area in 2015 there was no statistically significant differences in goods ($\chi^2_{1,\ 3,045} = 0.896$: $p > 0.05$) and service ($\chi^2_{1,\ 3,045} = 0.053$: $p > 0.05$) exporting, suggesting that rural SMEs in the NP perform as well as urban SMEs in terms of goods and service exports. However, in 2018 rural SMEs in the NP area were more likely to export goods than their urban counterparts ($\chi^2_{1,\ 2,780} = 4.858$: $p < 0.05$). Similarly, in the ME area in 2015, rural SMEs were more likely to report goods (χ^2_1, 2524 = 4.065: $p < 0.05$) and service exports ($\chi^2_{1,\ 2,511} = 17.41$: $p < 0.05$) than urban SMEs. In 2018, there were no statistically significant differences in exports of goods ($\chi^2_{1,\ 2,792} = 2.468$: $p > 0.05$); however, rural SMEs performed better than urban counterparts in terms of service exports ($\chi^2_{1,\ 2,793} = 3.985$: $p < 0.05$) in the ME area. When considering potential exports, rural SMEs were more likely to report that they had goods or services suitable for exporting than urban counterparts in the NP area in 2015 ($\chi^2_{2,\ 2,676} = 20.67$: $p < 0.05$) and in the ME area in 2018 ($\chi^2_{2,\ 2,318} = 22.79$: $p < 0.05$).

Regarding innovation, in 2015 there were no statistically significant differences in product ($\chi^2_{1,\ 3,047} = 1.537$: $p > 0.05$) and process innovation ($\chi^2_{1,\ 3,047} = 0.009$: $p > 0.05$) between rural and urban SMEs in the NP territory. In the ME area in 2015, rural SMEs were more likely to be engaged in product innovation ($\chi^2_{1,\ 2,525} = 7.667$: $p < 0.05$), but with no significant differences in process innovation ($\chi^2_{1,\ 2,512} = 0.477$: $p > 0.05$). Considering the 2018 data, rural SMEs in the NP were less likely to report being innovative in products than urban SMEs ($\chi^2_{1,\ 2,740} = 4.076$: $p < 0.05$). However, they reported higher levels of process innovation than urban SMEs ($\chi^2_{1,\ 2,751} = 3.852$: $p < 0.05$). In the ME in 2018, we found no significant differences between urban and rural SMEs regarding product innovation ($\chi^2_{1,\ 2,761} = 0.299$: $p > 0.05$), but rural SMEs were less likely to report being innovative in processes than urban counterparts ($\chi^2_{1,\ 2,775} = 4.429$: $p < 0.05$). Overall, considering urban and rural SMEs in the NP and ME territories as a whole there is no systematic or consistent evidence that an urban location stimulates higher rates of innovation and exporting.

However, a full comparison of business performance across locations requires controlling for differences in businesses' characteristics. To do this, we apply PSM. We begin in Table 3 by presenting the logistic regression models concerning the probability of a firm being located in a rural area in the NP (Model I and III) and ME (Model II and IV) areas. We perform a cross-sectional analysis using the data for the years 2015 and 2018. All models perform reasonably well since the Likelihood Ratio (LR) test evaluating the parameters of the covariates as a group (so analogous to the overall *F*-test for linear regressions) is highly statistically significant. The alternative Wald test, which performs the same function as the LR test, is also significant. The percentage of correctly classified businesses based on the propensity score is also reported and here it ranges between 71% and 80%, which is good (Olmuş et al., 2022).

In Table 3, the results of Model I reveal that rural SMEs in the NP area in 2015 are more likely than urban SMEs to be family businesses and to operate their businesses in wholesale and retail, transport and storage and accommodation and food service sectors. However, they are less likely to be younger firms (aged less than 5 years) or to be a sole trader than urban counterparts in this region. Similar results are found for Model II, with rural SMEs in the ME more likely to be family businesses, but less likely to be younger firms in 2015. Considering the 2018 analysis, the results for the NP (Model III) are similar to those of 2015, but rural SMEs are less likely to be small and medium sized businesses than urban firms. Rural SMEs in the ME area in 2018 (Model IV) were also more likely to be family businesses, but less likely to be medium-sized businesses than their urban counterparts.

Considering the match-paired comparison of business performance, Table 4 details the results of differences in exporting and innovation

Table 3
Probability of business being in a rural area – Logistic regression model.

Variable (DV = Rurality)	2015		2018	
	Model I (NP)	Model II (ME)	Model III (NP)	Model IV (ME)
	Coefficient (S.E.)	Coefficient (S.E.)	Coefficient (S.E.)	Coefficient (S.E.)
Constant	−1.327*** (0.228)	−1.233*** (0.208)	−1.497*** (0.211)	−1.377*** (0.191)
MICRO	−0.321** (0.158)	−0.061 (0.143)	−0.047 (0.140)	0.043 (0.127)
SMALL	−0.267 (0.165)	−0.046 (0.147)	−0.283* (0.162)	−0.202 (0.142)
MEDIUM	−0.109 (0.182)	−0.197 (0.164)	−0.355* (0.192)	−0.489*** (0.183)
WOMEN	−0.087 (0.144)	0.077 (0.126)	−0.199 (0.133)	−0.055 (0.119)
FAMILY	0.316** (0.139)	0.561*** (0.127)	0.435*** (0.126)	0.595*** (0.119)
SOTRADE	−0.297* (0.160)	−0.202 (0.157)	−0.170 (0.148)	−0.139 (0.142)
PROCN[a]	−0.023 (0.171)	0.105 (0.161)	0.214 (0.167)	0.298* (0.159)
TRANST	0.445*** (0.158)	0.156 (0.158)	0.431*** (0.158)	0.281* (0.156)
SERVICE	−0.099 (0.166)	0.169 (0.154)	−0.086 (0.164)	0.300** (0.150)
AGE05	−0.641*** (0.188)	−0.365** (0.159)	−0.364** (0.161)	−0.195 (0.139)
AGE20	−0.130 (0.113)	−0.165 (0.104)	−0.062 (0.106)	−0.116 (0.099)
Number of Observations	**2345**	**2180**	**2595**	**2445**
Correctly classified	**79.57%**	**70.78%**	**78.15%**	**70.35%**
Probability (LR-statistic)	**0.0000**	**0.0009**	**0.0000**	**0.0000**
Model Wald Statistic (χ^2_{11})	**43.59**	**31.47**	**50.08**	**56.69**

Notes: *, **, and *** denote statistical significance at 10%, 5% and 1%, S.E. is standard errors.
[a] We exclude farms from the analysis.

Table 4
Results of propensity score Matching – NP 2015 and 2018.

Matching technique	Model I (NP-2015)					Model III (NP-2018)				
	EXGOOD	EXSERV	PROTEX	GDINNO	PRINNO	EXGOOD	EXSERV	PROTEX	GDINNO	PRINNO
	ATET (SE)	ATET (SE)	ATET (SE)	ATET (SE)	ATET (SE)	ATET (SE)	ATET (SE)	ATET (SE)	ATET (SE)	ATET (SE)
PSM (1-to1)	−0.032** (0.016)	−0.003 (0.015)	0.025 (0.024)	0.022 (0.026)	−0.008 (0.023)	−0.001 (0.017)	−0.005 (0.014)	−0.012 (0.022)	−0.010 (0.021)	0.014 (0.021)
Nearest Neighbour (3)	−0.029** (0.016)	−0.004 (0.015)	0.024 (0.023)	0.023 (0.026)	−0.011 (0.023)	−0.001 (0.017)	−0.007 (0.014)	−0.010 (0.022)	−0.012 (0.021)	0.012 (0.021)
Caliper[a,b]	−0.030* (0.016)	−0.003 (0.016)	0.027 (0.024)	0.025 (0.026)	0.010 (0.023)	−0.002 (0.018)	−0.005 (0.014)	−0.014 (0.022)	−0.010 (0.022)	0.010 (0.020)
Number of obs	**2266**	**2340**	**1827**	**2345**	**2324**	**2584**	**2582**	**1960**	**2539**	**2554**
Matched	**958**	**958**	**768**	**958**	**942**	**1130**	**1128**	**868**	**1106**	**1118**
Variance ratio	**No significant difference**	**No significant difference**	**No significant difference**	**No significant difference**	**No significant difference**	**No significant difference**	**No significant difference**	**No significant difference**	**No significant difference**	**No significant difference**

Notes: *, **, *** denote significance at 10%, 5% and 1% level respectively, SE is standard error. ATET is average treatment effect on the treated.
[a] The width of Caliper equals to 0.2 of the standard deviation of the logit of the propensity score.
[b] The width of Caliper of Model II is 0.011 and that of Model IV is 0.012.

Table 5
Results of propensity score Matching – ME 2015 and 2018.

Matching technique	Model II (ME-2015)					Model IV (ME-2018)				
	EXGOOD	EXSERV	PROTEX	GDINNO	PRINNO	EXGOOD	EXSERV	PROTEX	GDINNO	PRINNO
	ATET (SE)	ATET (SE)	ATET (SE)	ATET (SE)	ATET (SE)	ATET (SE)	ATET (SE)	ATET (SE)	ATET (SE)	ATET (SE)
PSM (1-to1)	−0.017 (0.017)	0.018 (0.016)	−0.014 (0.024)	0.008 (0.026)	−0.007 (0.023)	−0.016 (0.016)	−0.008 (0.014)	0.031 (0.022)	0.007 (0.021)	−0.007 (0.019)
Nearest Neighbour (3)	−0.014 (0.017)	0.014 (0.016)	−0.011 (0.023)	0.005 (0.025)	−0.012 (0.021)	−0.015 (0.015)	−0.004 (0.014)	0.024 (0.021)	0.005 (0.020)	−0.010 (0.019)
Caliper[a,b]	−0.019 (0.016)	0.018 (0.016)	−0.013 (0.022)	0.007 (0.025)	−0.009 (0.022)	−0.015 (0.016)	−0.008 (0.015)	0.032 (0.022)	0.09 (0.021)	−0.009 (0.019)
Number of obs	**2179**	**2169**	**1627**	**2180**	**2250**	**2434**	**2437**	**1779**	**2402**	**2414**
Matched	**1274**	**1264**	**938**	**1274**	**1420**	**1446**	**1446**	**1094**	**1426**	**1434**
Variance ratio	**No significant difference**	**No significant difference**	**No significant difference**	**No significant difference**	**No significant difference**	**No significant difference**	**No significant difference**	**No significant difference**	**No significant difference**	**No significant difference**

Notes: *, **, *** denote significance at 10%, 5% and 1% level respectively, SE is standard error. ATET is average treatment effect on the treated.
[a] The width of Caliper equals to 0.2 of the standard deviation of the logit of the propensity score.
[b] The width of Caliper of Model II is 0.011 and that of Model IV is 0.014.

Table 6
Rural-urban analysis of innovation new to the market and new to the business.

	NP				ME			
	2015		2018		2015		2018	
	Rural	Urban	Rural	Urban	Rural	Urban	Rural	Urban
At least some new to the market	13.9%**	26.7%**	30.0%	34.2%	29.8%	23.2%	22.2%	30.1%
All just new to the business	86.1%**	73.3%**	70.0%	65.8%	70.2%	76.8%	77.8%	69.9%
Total	**101**	**404**	**110**	**325**	**114**	**298**	**99**	**286**

Note: Weighted percentages are given, and ** indicates a statistically significant difference (χ^2: $p < 0.05$).

between rural and urban SMEs in the NP area in 2015 and 2018. In 2015, there were no statistically significant differences in product innovation, process innovation, service exporting and potential exports. Rural SMEs were about 3 percent less likely to report exporting goods than their urban counterparts. In 2018, similar patterns prevailed regarding product and process innovation, potential exports, and service exporting, while in contrast to 2015, rural SMEs were also just as likely to have similar levels of exported goods as urban SMEs.

For the ME area (Table 5), the results consistently reveal no significant differences in goods or service exporting, potential exports, or product and process innovation between rural and urban businesses in 2015 and 2018.

Together, these findings indicate that rural SMEs perform as well as urban SMEs in the ME and NP areas regarding exporting and innovation, with no consistent support for Hypotheses 1 and 2. Specifically, there is no evidence that the level of innovation or exporting of a rural business in the ME or NP territories would have been substantially different if the same business had been located in an urban area rather than a rural one.

Finally, we distinguish between new to the market and new to the business innovation, which due to the small sample size we analyse by Chi square statistics (Table 6). For the NP region, rural SMEs were more likely to report new to the business innovation, but less likely to report new to the market innovation than urban SMEs in 2015 ($\chi^2_{1,\,505} = 7.306$: $p < 0.05$). However, there were no significant differences in new to the market and new to the business innovation between rural and urban SMEs in 2018. For the ME area, rural SMEs reported a similar level of new to the market and new to the business innovation as their urban counterparts in 2015 and 2018. Thus, on this measure, we again find no systematic differences between rural and urban SMEs in less prosperous regions.

5. Discussion

Rising spatial inequalities and their political effects have prompted increasing attention on strategies for Levelling Up 'left behind' localities (Tomaney and Pike, 2020). In England, this principally focuses on improving the fortunes of the less prosperous North and Midlands and closing the gap in incomes with London and the South-East (HM Government, 2022). In identifying the causes of disparities, the Levelling Up White Paper points to spatial variations in the endowments of six types of capital. In seeking to enhance capital endowments, drawing on agglomeration theory, the White Paper suggests that urban areas provide a more favourable environment for business innovation. However, empirical evidence on the relative performance of urban and rural SMEs in less prosperous regions remains limited. Addressing this evidence gap requires a consideration of both patterns for the overall stock of rural and urban businesses, as well as controlling for any differences in the structural characteristics of rural and urban businesses (sector, age, size etc.) to more precisely discern whether the performance of a rural business located in a less prosperous region would have been substantially different if the same business had been located in an urban area rather than a rural one. To undertake the latter analysis, we employed PSM and have drawn on data for SMEs located in the Northern Powerhouse (NP) and Midlands Engine (ME) territories.

Considering first the stock of rural and urban businesses in both areas (Table 2), we assessed their comparative performance in terms of product and process innovation as well as exports of goods and services using LSBS data for 2015 and 2018. These results can be compared against previous findings (Hindle et al., 2010; North and Smallbone, 2000), albeit recognising differences in geographical coverage, timeframe, sampling, and analytical procedures across studies. Regarding process and product innovation, we find no evidence of urban firms consistently achieving better results, which is consistent with an analysis for English small firms by Hindle et al. (2010). However, in both the NP and ME regions only a minority of SMEs introduced either product or process innovations and, worryingly, in both regions it appears that innovation rates fell between 2015 and 2018, with little evidence to suggest that policy attempts to stimulate SME innovation are changing the levels of business innovation dramatically. Regarding exporting, on no outcome measure do urban SMEs as a group in either the NP or ME areas perform better than their rural counterparts and considering the overall stock of businesses in the UK, rural SMEs were more likely to export than urban firms and have greater export potential. This is consistent with previous evidence, albeit based on smaller samples, of a lack of superiority of urban SMEs in the UK regarding patterns of exporting (Westhead et al., 2004).

The PSM analysis provides a further assessment of the effect of a rural location on business innovation and exporting as it allows for a comparison of urban-rural businesses that are more similar across a set of characteristics. For the 2018 dataset, the PSM results suggest that in the NP region there were no significant differences on any performance measure between urban SMEs and their rural counterparts and this result holds irrespective of the type of matching approach employed. For 2015, the PSM analysis indicates a similar pattern apart from rural SMEs being less likely to report that they have exported goods compared to urban counterparts in the NP region. Regarding the magnitude of this difference, it is worth remembering that the treatment effect is a difference in means between the two groups being compared, so with all three matching methods it is evident that for NP rural businesses there is about a 3% percentage point lower propensity to have exported goods in comparison with NP urban businesses in 2015.

In the ME, for both the 2015 and 2018 PSM analysis, there were no significant differences on any performance measure between urban SMEs and their rural counterparts. Collectively the results indicate *no systematic negative rural effect on SME innovation and exporting across the NP and ME regions* whilst also suggesting extra, but yet untapped, export potential in rural areas.

It is interesting to reflect on why the empirical evidence does not support the hypothesized relationships based on agglomeration theory set out earlier in the paper. Here, three potential explanations warrant discussion. Firstly, the strongest evidence of agglomeration effects, in terms proximity aiding business innovation, exists for high tech, high skilled industries in prosperous regions (Fujita et al., 2001). It may be that such enterprises represent a smaller percentage of the total businesses in less prosperous regions. Secondly, it may be that any agglomeration benefits are counteracted by other forces which affect the accumulation and combination of capitals. For example regarding human capital, the lure of a more appealing living environment, especially to raise a family, facilitates the attraction and retention of higher skilled workers and entrepreneurs to rural areas (Bosworth and Bat Finke, 2019), who often bring with them extensive network capital which can aid business innovation and growth (Bosworth and Bat Finke, 2019). Finally, the increasing digitalisation of connections may reduce agglomeration benefits. Specifically, reliance on face-to-face interactions is falling, with the need for cities as central hubs increasingly questioned (Bartik et al., 2020). While our data relates to the pre-Covid-19 pandemic period, the latter highlighted how greater digital connectivity is opening up rural areas to stronger competition, which can spur innovation, and also enable rural enterprises to more easily exchange knowledge, recruit high skilled remote workers, and compete in more distant geographical markets, including internationally (Ri and Luong, 2021). Consequently, digitalisation may diminish urban areas' advantages in terms of matching, sharing, and learning (Duranton and Puga, 2004).

Regarding linkages with other policy objectives, the Levelling Up agenda in the UK links to "Global Britain" campaigns to increase exports (Wincott, 2020), particularly in markets outside of the European Union (EU). However, in the NP and ME regions less than one in ten SMEs export and there is typically more than double the number of SMEs which say they have goods and services suitable for export than actually do so. While differences in sample composition limit comparable analysis, there appears to be little evidence of substantial changes in SME export rates between 2015 and 2018, and also compared with earlier evidence (years 2011–2014) from the UK Annual Business Survey (ONS, 2015). Overall, considerable latent, unrealized export potential appears to exist. This problem (or opportunity) is common to rural and urban SMEs in the NP and ME regions, and especially pronounced in rural areas.

It is interesting to compare the results presented here relating to new to the world innovation with the findings of Roper (2020) concerning patent, trademark and design (PTMD) intensity. Roper (2020) finds that rural areas are associated with a significantly lower PTMD intensity, while here we find only evidence of significantly lower new to the world innovation for the NP case in 2015. Three factor may explain this apparent discrepancy. Firstly, the analysis of Roper (2020) is England wide, so includes London and the rest of the South-East regions, which have the highest levels of PTMD intensity in the UK (Intellectual Property Office, 2019), rather than just the NP and ME regions. Generally, analysis of urban-rural differences in UK business performance are sensitive to whether the former category includes or excludes London, as a world city with markedly higher levels of business productivity and start-up rates than the rest of the UK (Defra, 2021). Secondly, our analysis for the ME and NP regions covers new to the market innovation, which is a broader term than registration of patents, trademarks and designs. Freshwater et al. (2019) argue that innovation often follows different paths in urban and rural SMEs, with the latter less likely to embrace formal registration systems, but rather focus on 'informal' innovations which benefit the firm and its direct customers. Lastly, the analyses employ different econometric techniques, business size thresholds, and also definitions of rural which limits cross-comparison. For instance, this study follows the ONS (2013) classification of localities, so that urban-rural is treated as a binary variable while Roper (2020) employs a continuous variable based on a classification of Lower Super Output Areas according to population density and journey times to city centres.

6. Conclusion and future research

Regional variations in incomes are persistent and growing, prompting attempts to "level up" less prosperous localities (McCann and Yuan, 2022). This agenda generates questions regarding the role of rural areas in regional initiatives (Turner et al., 2021). Generally, rural areas are often overlooked in debates on Levelling Up (Pragmatix Advisory, 2022), with the focus on cities justified based on theories of agglomeration (HM Government, 2022). However, analyses of the performance of SMEs located in the NP and ME areas, based on a novel application of treatment effect analysis, indicates no systematic evidence of a negative rural location effect. Rather, rural firms are as likely to export and innovate as their urban counterparts. Therefore, policies for enhancing regional performance should adequately recognise the current contribution of rural businesses as well as their potential (for instance regarding goods and services suitable for exporting which are currently not sold overseas).

This study highlights several avenues for future research. Firstly, due to data limitations, this study draws on cross-sectional analysis for the years 2015 and 2018. Future research would benefit from a longitudinal analysis, employing panel estimation, to better understand the relationships between the rural and regional effects and innovation and export performance over time. Secondly, future research, when data becomes available, should also consider the impact of Brexit on export performance, and how this may vary regionally and between rural and urban areas. While aggregate data to date indicates that Brexit has significantly affected SME's international trade (ONS, 2022), especially for food and agricultural sectors, which are relatively more important in rural areas, firm level analysis could provide a richer picture of the determinants of disruption and resilience. Thirdly, the LSBS contains only binary measures of innovation, so we do not capture the intensity of innovation (e.g., the number of new products/services or processes), and we lack data on accumulated innovation. A similar issue relates to exporting. Future research would benefit from more detailed assessments of business innovation and export intensity. Finally, since the data analysed in this paper were collected before the Covid-19 pandemic, it would also be interesting for future studies to explore the impact of the Covid-19 crisis on business innovation and exporting. This should consider the extent to which impacts vary spatially, alongside evaluating the effectiveness of government measures seeking to support SMEs during the pandemic.

Data availability

The authors do not have permission to share data.

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Appendix A. Supplementary data

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