OECD Regional Development Working Papers

Agglomeration Economies in Great Britain

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This paper estimates agglomeration economies in Great Britain. The analysis employs a definition of urban areas as functional economic units developed by the OECD in collaboration with the European Union to investigate the size and sources of productivity disparities across urban areas. It uses data from the UK Annual Survey of Hours and Earnings and the UK Labour Force Survey between 2000 and 2018 and a two-step estimation procedure that accounts for bias in the extent of agglomeration economies arising from individual sorting. The results suggest that a 10% increase in employment density of a city in Great Britain, would, on average, increase city productivity by 0.9-1 percent. The analysis also shows the estimated elasticity for employment density remains the same before and after the 2007–08 global financial crisis, not showing any clear structural break between city size and productivity relationship.

Keywords: Local labour markets, spatial wage disparities, Great Britain
JEL codes: R12, R23, J31

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1 Introduction

Cities are a key driver of their regions' economic performance and productivity growth. In today's digital and service economy, cities enable interactions between individuals that generate growth through transformative and knowledge-intensive industries. As the world becomes more urbanised, the productivity of cities is becoming an essential determinant of countries' productivity. Given the need to raise the potential for long-term growth, understanding how to increase the productivity of these cities is, therefore, an urgent policy question.

In the past two decades, a substantial body of evidence has accumulated providing robust evidence showing that in many parts of the world, the economic productivity of a city increases with its population size (Rosenthal and Strange (2004[2]); Combes and Gobillon (2015[3]). The sorting of workers partially drives this effect as individuals with higher abilities and education tend to live and work in larger cities. However, even beyond this compositional effect, the productivity of a given individual increase with the size of the city in which they work.

There are large inequalities across the regions in Great Britain. These regional inequalities (or the so-called "North-South divide") go back in time and can be traced back to the 1920s and 1930s (Gardiner et al., 2013[4]). The deindustrialisation during the 1980s and 1990s have led to a decoupling in the economic performance of the UK economy and London, further increasing the regional disparities. While London compensated the loss of manufacturing by specialising in finance and insurance sector, other cities have struggled to build strong economic specialisations that could compensate for the decline of old industries. Consequently, in 2016, London, which was home to 18.3% of the UK's population, generated 28.1% of the total GDP of the UK economy. While substantial spatial inequalities exist in almost every metric (i.e., production, life quality, etc.), the productivity difference between the most and the least productive regions are one of the highest among the OECD countries (OECD, 2017[5]). Moreover, these regional disparities have been increasing since the early 2000s and have further steepened since the 2007-08 global financial crisis (OECD, 2015[6]) (OECD, 2017[5]).

This paper studies the sources of spatial differences in productivity by focusing on agglomeration effects in Great Britain and has two main objectives: First, this study applies a standard methodology to provide elasticities that are comparable to estimates from other countries. Given that estimates on agglomeration economies are sensitive to data choice, sample selection and specification, the use of standard methodology is essential for obtaining comparable elasticities (Melo, Graham and Noland, 2009[7]). Second, given the productivity slowdown observed in the UK since the Great Recession, the paper aims to explore whether agglomeration economies can partially explain the slowdown. Specifically, the study compares the strength of the agglomeration economies before and after the the global financial crisis.

This paper aims to take upon the challenge of explaining the determinants of wages disparities across cities in Great Britain by applying the standard two-step methodology proposed by Combes et al. (2008[8]). The analysis uses individual-level data for a large panel of British workers for the period 2000 to 2018. The panel data is a 1 percent sample of all registered employees who are subject to social security contributions and provides a large set of individual characteristics and Local Urban Authority (LAU) where the individual is located. The location of the workers is matched with the EU-OECD Functional Urban Area (FUA) definition to identify residents of the 93 FUAs with 70 000 to 12.8 million inhabitants in 2018.[1] In a first step, micro-data on wages is used to estimate city productivity premiums net of skill and industry composition, as captured by wage-premiums, for each city in Great Britain. In a second step, the paper explores the determinants of these estimated city productivity premiums, by looking at the role of employment density, human capital externalities, land area, industrial diversity and accessibility of cities to their surrounding areas.

According to the preferred estimates that account for individual sorting, the elasticity of urban area productivity with respect to employment density is 0.01. This means that– roughly speaking – a 10 percent increase in employment density increases productivity by 0.1 percent. [2] This elasticity is one of the smallest one found in the literature and it is in line with the earlier findings for Great Britain.

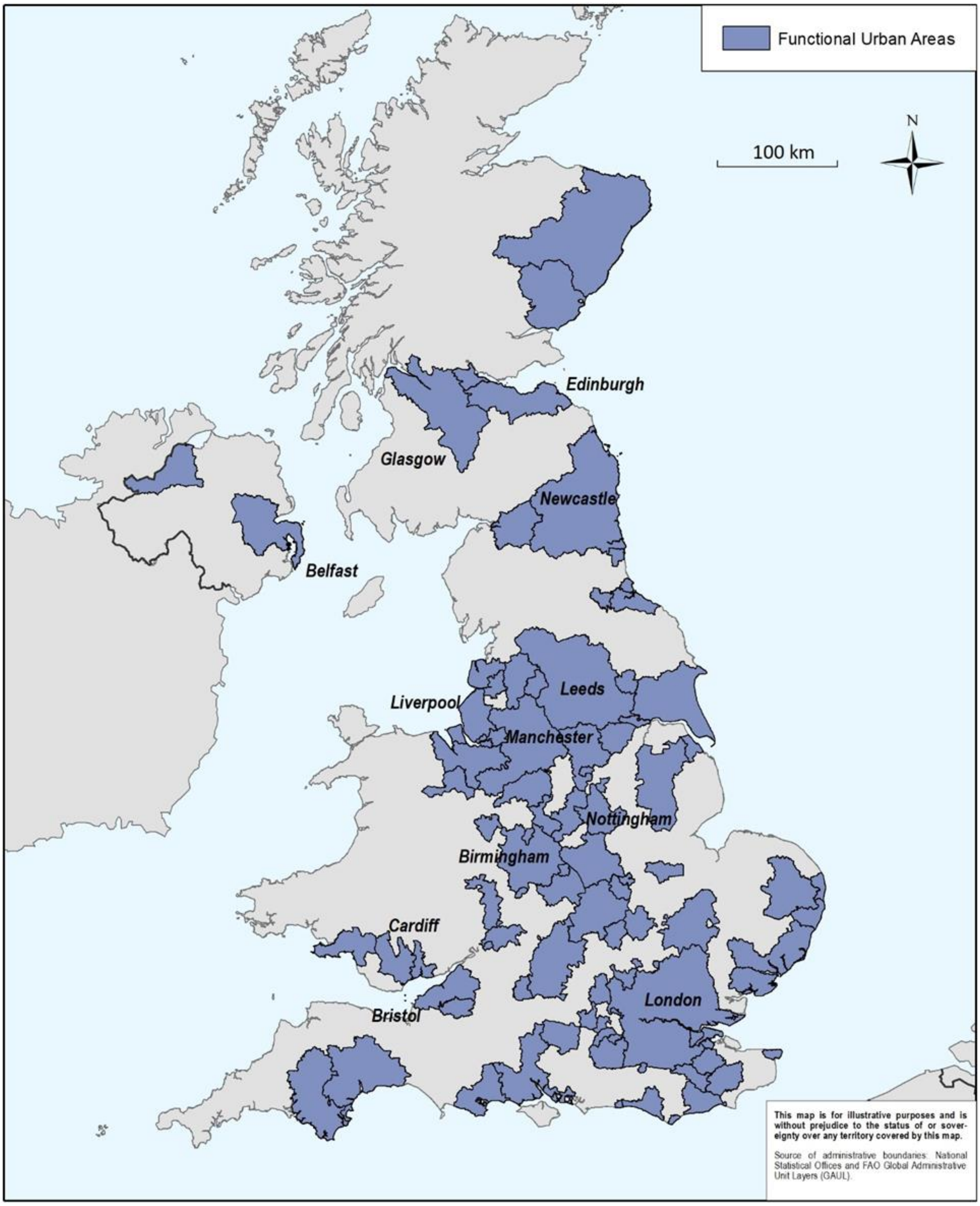
The analysis also shows that surface of an urban area is associated with higher productivity. Holding employment density constant, the larger land area – which means a larger population - allows more non-market interactions among agents and generate productivity gains. Higher human capital levels in cities calculated as the share of the workers with a university degree or above in the overall workforce have a positive and statistically significant effect. The estimated elasticity indicates that a 10 percent increase in the share of university graduates is associated with a 1.7 percent increase in productivity of the overall workforce. Having better accessibility to other cities and regions is an important determinant of a city's productivity. Empirically, the analysis shows that a 10 percent increase in the road accessibility performance of a city increases the average productivity by 1.2 percent. Industrial diversity does not have any statistically significant effect on productivity. Finally, when splitting the observations before and after the crisis, the estimated elasticities for employment density remain the same, thus not showing any clear structural break between city size and productivity relationship.

The paper is organized as follows. The next section presents a brief review of the agglomeration literature. Section 3 presents the empirical strategy and Section 4 presents the data used in the analysis. Section 5 provides estimates on density and other determinants of productivity, last section concludes.

[1] All the results presented in this report are at FUA level; see Box 1 for further details on FUAs and see Figure 1 for a map of FUAs in the UK. Although there are 95 FUAs in the UK, the analysis excludes 2 FUAs located in the Northern Ireland due to data constraints. Terms city and FUAs are used interchangeably across the text.

[2] Since the seminal work of Ciccone and Hall (1996[29]) the size of the local economy is measured by the number of employment per unit of land, i.e., density. This measure is preferable to using level of local population or employment as it addresses other issues related to spatial extent of the geographic unit and mismeasurement (Combes and Gobillon, 2015[3]). This study measures local economy size by density to provide estimates that are comparable with the literature.

Figure 1. Boundaries of FUAs in the United Kingdom



Note: This map shows the boundaries of Functional Urban Areas (FUA, the OECD's definition of travel to work areas, see Box 1 for a definition). Due to data issues, the analysis excludes two FUAs located in the Northern Ireland.

2 Literature

The idea that larger cities enjoy a productivity advantage dates back to Marshall (1890[9]), who argued that larger markets benefit from more intensive input-output linkages, thicker local labour markets, and technological spillovers between firms which in return increase the average productivity. The large theoretical and empirical literature on agglomeration economies show that larger cities have higher productivity as their market size facilitates sharing, learning or matching (Duranton and Puga, 2004[10]).

An important reason for the higher productivity observed in larger cities is due to sorting of workers with higher abilities to larger cities. Glaeser and Maré (2001[11]) were the first to test this idea by controlling for individual characteristics such as education and age, but also introducing individual fixed-effects when studying the effect of density across US cities. The use of individual fixed-effects is important as it allows controlling for all of the time-invariant factors related to an individual's ability (e.g. grit, intelligence, and more) that influences her productivity, which is otherwise unobservable in the data. Using individual controls and fixed-effects allows capturing the effects of local characteristics that are net of composition effects due to sorting of an individual with higher abilities to larger cities.

Using a much larger panel for workers, Combes et al., (2008[8]) estimate the effect of density on wages across all French cities including individual fixed-effects and taking into account aggregate endogeneity using a two-step estimation procedure involving instrumentation. They find an elasticity of wages with respect to the density of around 0.030, which is half the elasticity that is obtained when individual unobserved heterogeneity is not taken into account. Using approaches accounting for individual heterogeneities through fixed-effects or controls, similar elasticities are found for European economies (e.g., 0.025 for Spain (De la Roca and Puga, 2017[12]); 0.01 for Italy (Mion and Naticchioni, 2009[13]); 0.016 for Britain (D'Costa and Overman, 2014[14]); 0.021 for Netherlands (Groot, de Groot and Smit, 2014[15]).

Box 1. Defining local labour markets

Functional urban areas

Cities are the natural starting point to analyse the impact of agglomeration on productivity. However, local labour markets extend beyond the administrative boundaries. For example, many people who work in central London, commute to work from its surrounding municipalities. Likewise, manufacturing sites that are located on the outskirts of a city could require their workers to commute out. Using administrative boundaries to define the extent of local labour markets would generate a bias as it would misallocate the production of commuting workers to their place of living and not to place of work, generating a mismeasurement. Defining local labour markets based on commuting patterns would reflect the functioning economy of that city and would avoid this bias. More generally, focusing on the local administrative unit of a city will underestimate the population size of an urban area, overestimate the density, and might over- or underestimate its productivity.

To capture labour market dynamics of a city, the study relies on a functional definition of cities or “Functional Urban Areas” (FUAs) that combines information on the urban built-up area with commuting flows (Brezzi et al., 2012[16]). FUAs are cities with at least 50 000 inhabitants living in a contiguously built-up area with at least 1 500 inhabitants per 1 km^2. These built-up areas are matched with the smallest available statistical or administrative unit in a country – local authorities in the UK – to form the urban centre of an FUA. To complete the FUA definition, the less densely populated commuting zone around the urban centre is identified by considering all local authorities with at least 15 percent of their population commuting to the urban centre as part of the FUA.

3 Empirical strategy

This section presents the framework for estimating the agglomeration effects in Great Britain. It outlines in detail both steps of the estimation strategy.

First-step: Accounting for individual selection into FUAs

In the first-step, individual-level microdata and OECD-EU definition of FUAs are matched. The resulting data set is then used to estimate productivity differentials – net of skill and industry composition – across FUAs using an OLS regression where the natural logarithm of wages is regressed on individual-level characteristics and a set of fixed-effects.

$$y_{irst} = \alpha + \beta Spe_{rst} + \Phi X_{it} + \gamma_s + \gamma_{rt} + \gamma_i + \varepsilon_{irst} \quad (1)$$

y_{irst} denotes the natural logarithm of wages for individual i in city r employed in sector s at time t. Spe_{rst} captures the effect of specialisation in a given sector on productivity, X a vector of individual observable characteristics (e.g., education, sex, age, occupation, and more) and employment characteristics (e.g., full-time, collective bargaining, or public sector). γ_{rt} is the city-time fixed effects and γ_s is a sector fixed-effect. γ_i is individual fixed-effect. ε denotes the error term.

A certain degree of specialization generates within-industry externalities and creates faster growth through spillovers (Combes and Gobillon, 2015[3]). Productivity gains from specialisation emerge because the workforce's skill set matches the needs of the industry better and because innovations spread faster across firms within the same industry than across firms in different industries. In contrast to other benefits from agglomeration, the gains from specialisation are specific to the specialised industry (Özgüzel, 2019[17]). To capture such positive spillovers, *Specialisation* variable is constructed as the share of employees working the industry in the total workforce.

A set of Mincerian controls are added to account for individual characteristics that may influence individual productivity or nominal wages. Individual fixed-effects, on the other hand, allows controlling for the "sorting bias" where individuals with higher unobservable abilities (e.g., higher levels of motivation or grit) sort into larger cities.

The sector fixed-effects absorb structural productivity differences between industries that is constant across time. Specialisation and sector-fixed effects together control for observed and unobserved industry effects.

Inclusion of these controls and fixed-effects allow netting out the effects of skill and industry composition when estimating the city-year fixed effects, which can be interpreted as the local wage indices. Put differently, the city-year fixed effects ($\widehat{\gamma_{rt}}$) obtained in the first-step capture productivity differential across cities, net of (observable and unobservable) skill differences and the industry structure of the local economy.

Second-step: Explaining FUA productivity differentials

The estimated productivity differentials ($\widehat{\gamma_{rt}}$) are used as the dependent variable in the second-step, in which they are regressed on time-varying city characteristics (Qrt). Additional year-fixed effects γ_t control for national business cycles and country-specific inflation as the first-step estimates nominal productivity differentials.

$$\widehat{\gamma_{rt}} = \beta Q_{rt} + \gamma_t + \varepsilon_{rt} \text{ (2)}$$

There is a range of city characteristics (Q_{rt}) considered in this study. The main variable of interest is the employment density, measured as the level of local employment divided by land area, and it captures the productivity gains associated with larger city sizes.

Human capital levels are one of the most important determinants of productivity. Higher levels of education can boost productivity of the worker and translate into higher wages. These private gains are captured in the first-step through inclusion of education. Workers that are more educated also have positive effects on the productivity of their co-workers, an effect that economists call a positive externality (Moretti, 2004[18]). To capture human capital externalities arising from differences in the skill composition of the local population, the share of university degree holders in the 25-64 aged population of the FUA is used as a measure of the human capital. Note that given that individual skills are controlled in the first-step through individual controls and fixed-effects, this variable captures the positive spillovers arising from the presence of a skilled population.

Diverse economies benefit from cross-industry knowledge spillovers and cross-industry fertilization, the so-called Jacobsian economies, which is a source of innovation and growth (Combes and Gobillon, 2015[3]). These positive effects are especially beneficial when the diversification involves economic activities that are "related", meaning that they have similar characteristics but are not identical (Xiao, Boschma and Andersson, 2018[19]). Although various measures exist to capture such possible spillovers, the most commonly used measure is the Herfindahl index of employment shares at the 2-digit industry level, which is used as controls for the industry structure of cities. The Herfindahl index is defined for each FUA as the sum of the squared employment shares in each industry.

Having better accessibility to other cities and regions is an important determinant of a city's productivity. A city that is better connected to the rest of the country can provide better market access to firms and allows them to export at a lower cost (Krugman, 1980[20]). Likewise, it also reduces the local prices of imports, which increases efficiency and consumer welfare (Krugman and Venables, 2006[21]). Road accessibility is measured as the share of people that can be reached within a 90-minute drive from the city relative to the number of people living in the area that is potentially accessible (European Commission, 2018[22]). Cities that have better road infrastructure or good connections to motorway networks provide access to large population concentrations allowing higher accessibility. While the econometric analysis used road accessibility for data availability reasons, it is likely that accessibility by other modes of transport has equally important effects.

Finally, the standard errors are clustered at the FUA-level to allow for heteroscedasticity and arbitrary autocorrelation over time (for each FUA) in the error term.

Box 2. Endogeneity concerns

Estimating the effect of local characteristics on workers' productivity can suffer from endogeneity (also known as reverse causality) that can be both at the individual level and at the local economy level.

The endogeneity at the individual level is what the literature calls the "sorting effect" where the workers with higher abilities (e.g. higher education or motivation) choose to live in larger cities. Literature shows that sorting effects can be very important and cause overestimation of productivity gains of agglomeration. The use of individual micro-data and introduction of individual controls and individual-fixed effects allow addressing this endogeneity concern (Combes and Gobillon, 2015[3]).

The characteristics of the local economy can also be endogenous to workers' productivity. Reverse causality is an issue when higher local average wages attract workers, and this increases the quantity of local labour and thus city size. In that case, one expects a positive bias in the estimated coefficient of city size. The literature has attempted to address the endogeneity at the local level using several alternative strategies. A simple approach consists of including time-invariant local fixed effects in specifications estimated on panel data to deal with missing local variables that increase the productivity (such as being located by the seaport or having fertile lands) that are constant over time. Some authors instrument the local determinants of agglomeration economies using additional variables such as local historical or geological variables.

Correcting for this endogeneity is generally found to have a small effect on estimated elasticities. For instance, instrumentation decreases the elasticity of city size (or density) by 10 to 20 percent, and sometimes leaves the estimates unaffected or may even make them slightly increase. By contrast, using individual data and introducing individual fixed effects to control for spatial selection can change the estimated elasticity of productivity with respect to a density much more. For instance, according to (Combes, Duranton and Gobillon, 2008[8]), when individual sorting is not taken into account the coefficient on density is overestimated by nearly 100 percent. Depending on the country and on the precise methodology used to control for skills (individual fixed effect or observed skills variables), the magnitude of the sorting bias can vary significantly (Combes and Gobillon, 2015[3]).

The analysis in this report takes into account endogeneity concerns at the individual level which is the main source of bias in such estimates. It does not address the potential reverse causality between productivity and local characteristics. However, given the small magnitude of reverse causality that is usually found, this is unlikely to affect the estimates strongly.

4 Data

The estimation of the first-step is based on data from the UK Annual Survey of Hours and Earnings (ASHE) and its predecessor the New Earnings Survey (NES) which covers the period 2000-2018. ASHE is the largest survey of workers in the UK with approximately 160,000 employees a year. It is constructed by the Office of National Statistics (ONS) based on a 1 percent sample of employees on the Inland Revenue Pay as You Earn (PAYE) register for February and April. ASHE provides information on individuals including their home and work postcodes, while the NES provides similar data, but only reports work postcodes. The sample is of employees whose National Insurance numbers end in two specific digits (these have been the same since 1975), meaning ASHE provides an individual level panel, in which workers are observed for multiple years. The sample is replenished as workers leave the PAYE system (e.g., to self-employment) and new workers enter it (e.g., from school).

The data provides detailed information on individual earnings including basic pay, overtime pay, basic and overtime hours worked. The analysis uses basic hourly earnings as the wage measure. Moreover, ASHE includes information on other individual characteristics, such as occupation (Standard Occupation Classification, SOC), industry (Standard Industrial Classification, SIC), whether the job is in the private or public sector, the worker's age and gender. Information on education is not available via ASHE and thus it is imputed using the U.K. Quarterly Labour Force Survey for 2000–2017.[3]

Appendix Table A1 presents descriptive statistics of individuals in ASHE for individuals residing in the 93 FUAs during the period 2000-2018. According to Appendix Table A1, base hourly earnings in the sample during this period is around 12.5 pounds, half of the individuals are male, whereas the average age is around 42.5 years. Moreover, around 67 percent of employees have completed upper secondary education and around 41 percent have completed university. While 78 percent of individuals in the sample are in full-time employment, 35 percent are working in the public sector and 53 percent are part of a collective agreement. In terms of industry composition, around 66 percent working in the services (Distribution, hotels, and restaurants; Transport and communication; Banking, finance, insurance and business services and leasing; other services) while 17 percent work in construction and 4 percent in manufacturing. There is a roughly uniform distribution of employees across the 8 major occupation groups.

The estimation of the second-step employs as explanatory variables FUA characteristics that have been identified as significant predictors of productivity in the literature (Glaeser and Maré, (2001[11]); Combes et al., (2008[8]). For the purpose of our analysis, information on these characteristics was drawn from the Quarterly Labour Force Survey (QLFS) for the same period as that for the ASHE data. The QLFS is the largest household study in the UK based on a representative sample of the population in the UK and provides the best source of information on individual characteristics, such as education, as well as employment and unemployment. It also includes detailed geographical area information for each individual at the most disaggregated, such as postcodes. This, combined with the sufficiently large number of observations at the area level allows us to produce precise measures of FUAs characteristics. We identified FUAs in the QLFS data using statistical ward information and data from the OECD that matches statistical wards into FUAs.

[3] See Appendix for further details on the data preparation procedure.

Variables such as population, employment density, the share of graduates and Herfindahl index are calculated using ASHE data. The data set is complemented by a road accessibility index which measures the share of people that can be reached within a 90-minute drive from the city relative to the number of people living in the area that is potentially accessible. The index is prepared by the European Commission (2018[22]) and is available for many cities across the European Union.

Appendix Table A2 presents descriptive statistics of key characteristics of UK FUAs as calculated using the QLFS data. Based on Appendix Table A2, the average FUA population is 916 000, the average area is around 790 km², and, on average, around one-fifth of the population has a university degree. Moreover, the Herfindahl index measuring industry concentration, at the two-digit level is 0.07, suggesting relatively low concentration. On average cities have road performance of 87.9 percent which means that firms located in an FUA can on an average reach to 11.9 million customers within an hour and half of drive.

5 Results

Determinants of variations in hourly wages

Before presenting regression results, it is informative to analyse the sources of spatial variation in wages.[4] To do so, the nominal wages are regressed on different sets of explanatory variables (location effects, individual characteristics, and firm characteristics) and fixed-effects to understand their relative contribution to monthly wages.[5] Table 1 reports the adjusted R^2 of each regression.

Individual characteristics, such as age, sex, education, occupation and experience, alone explain 55 percent of the variations in individual wages across UK cities. The fact that individual characteristics matter for wages and productivity is now well documented for the UK (D'Costa and Overman, 2014; Gibbons, Overman and Pelkonen, 2014) and other developed countries such as France or the US (Combes, Duranton and Gobillon, 2008; Baum-Snow and Pavan, 2012). The explanatory power of firms, which includes only sector dummies and public sector dummy as explanatory variable, is around 8.5 percent. City effects, which includes FUA dummies and specialisation index, explain around 5.2 percent of the variation in wages. These results suggest that individual characteristics are the main factors explaining individual wage disparities, followed by firm and city characteristics. Compared to findings for France in Combes et al., (2008[8]), while the low explanatory power of firm characteristics is similar, the effect of city characteristics on wage disparities is half of what was observed for France.

These results reveal that individual characteristics and FUA effects are fairly orthogonal. Individual characteristics and FUA effects together explain 58 percent of the wage disparities when the sum of their individual is R^2 of 61 percent. On the other hand, firm characteristics and FUA effects explain 14 percent of the variation which corresponds to the sum of their individual R^2. Finally, the explanatory power of all three sets of explanatory factors is around 59 percent, which suggests that the main source of variations of wages in the UK is due to individual characteristics, and cannot be attributed to the differences in the composition of the city or firm characteristics.

[4] Productivity is the efficiency with which firms convert inputs (labour, capital, and raw materials) into outputs. When productivity increases, it allows increasing the output faster than the inputs. Although there are a number of ways to measure productivity, the two most commonly used productivity measures are Labour Productivity and Total Factor Productivity (TFP). Similar to the literature, this paper uses hourly wages as proxy for labour productivity.

[5] This approach is used for a similar exercise in Gibbons et al. (2014[27]) for the UK, in Combes et al., (2019[28]) for China and in Özgüzel (2019[17]) for Turkey.

Table 1. Explanatory power of various sets of variables

Adjusted R-squares for individual wages for the period 2000-2018

Individual Characteristics	0.558
Firm Characteristics	0.085
City Effects	0.052
City effects and Individual Characteristics	0.579
City Effects and Firm Characteristics	0.138
Individual Characteristics and Firm Characteristics	0.559
All three sets	0.593
Observations	1,988,855

Note: Table presents adjusted R-squares for individual wage regressions using data for the period 2000-2018.
Source: OECD calculations based on the UK Annual Survey of Hours and Earnings (ASHE) microdata.

First-step regressions

Table 2 presents first-step estimation results employing different specifications of equation (1). Estimates of coefficients of characteristics in column (1) of

Table 2 includes a small set of controls for individual characteristics compared to the other specifications. In line with the literature, the results show a significant male wage premium, significantly higher earnings among those with higher educational qualifications and those who employed full-time. Moreover, results suggest that individual earnings increase, at a decreasing rate, with the years of working experience, as measured by age.

Column 2 includes industry-fixed effects to account for time-invariant differences in productivity across sectors. In column 3, dummy variables indicating if the individual is working in the public sector or in a job that is covered by a collective agreement are added. Both are positively and significantly associated with individual earnings. Finally, industrial specialisation has positive effects on the productivity and wages of workers who are employed in the same sector.

As outlined above, the panel nature of the available data allows the estimation of fixed-effect models in the first-step. Column (4) includes individual fixed-effects to control more tightly for time-invariant individual productive characteristics that may produce differential returns across areas. As discussed in the previous section, controlling for unobservable characteristics of the individual aims to address estimation bias due to the sorting of individuals into denser and larger areas.

Table 2. Individual determinants of productivity

First-Step Regression Results for Individual Log Basic Hourly Earnings; 2000-2018

	(1)	(2)	(3)	(4)
VARIABLES	Log(wages)	Log(wages)	Log(wages)	Log(wages)
Sex	0.1016***	0.0983***	0.0987***	
	(0.0014)	(0.0014)	(0.0014)	
Upper Secondary	0.0174***	0.0158***	0.0159***	
	(0.002)	(0.002)	(0.002)	
University	0.0800***	0.0803***	0.0805***	
	(0.0021)	(0.002)	(0.002)	

Postgraduate	0.0859***	0.0858***	0.0874***	
	(0.0024)	(0.0023)	(0.0023)	
Age	0.0398***	0.0391***	0.0385***	0.0334***
	(0.0003)	(0.0003)	(0.0003)	(0.0008)
Age squared	(0.0004***	(0.0004***	(0.0004***	-0.0005***
	(0.0000)	(0.0000)	(0.0000)	(0.0000)
Full time	0.0864***	0.0804***	0.0792***	0.0062***
	(0.0012)	(0.0012)	(0.0012)	(0.0012)
Collective agreement			0.0163***	0.0096***
			(0.0009)	(0.0007)
Public sector			0.0572***	0.0295***
			(0.0016)	(0.0018)
Log(specialisation)	0.0057***	0.0560***	0.0547***	0.0219***
	(0.0008)	(0.0014)	(0.0014)	(0.0011)
Observations	1,148,778	1,148,778	1,148,778	1,148,778
R-squared	0.6386	0.6481	0.6495	0.9028
Occupation dummies	Yes	Yes	Yes	Yes
Industry dummies	No	Yes	Yes	Yes
Area-Year Fixed Effects	Yes	Yes	Yes	Yes
Individual Fixed Effects	No	No	No	Yes

Note: Table reports OLS estimates for the first-step of the estimation. The dependent variable is the log of nominal wages, regressed on individual characteristics, specialisation index, area-year fixed effects (not reported) and industry-fixed effects (not reported). The unit of observation is the individual. Standard errors are clustered at area level. *** p<0.01, ** p<0.05, * p<0.1
Source: OECD calculations based on the UK Annual Survey of Hours and Earnings (ASHE) microdata.

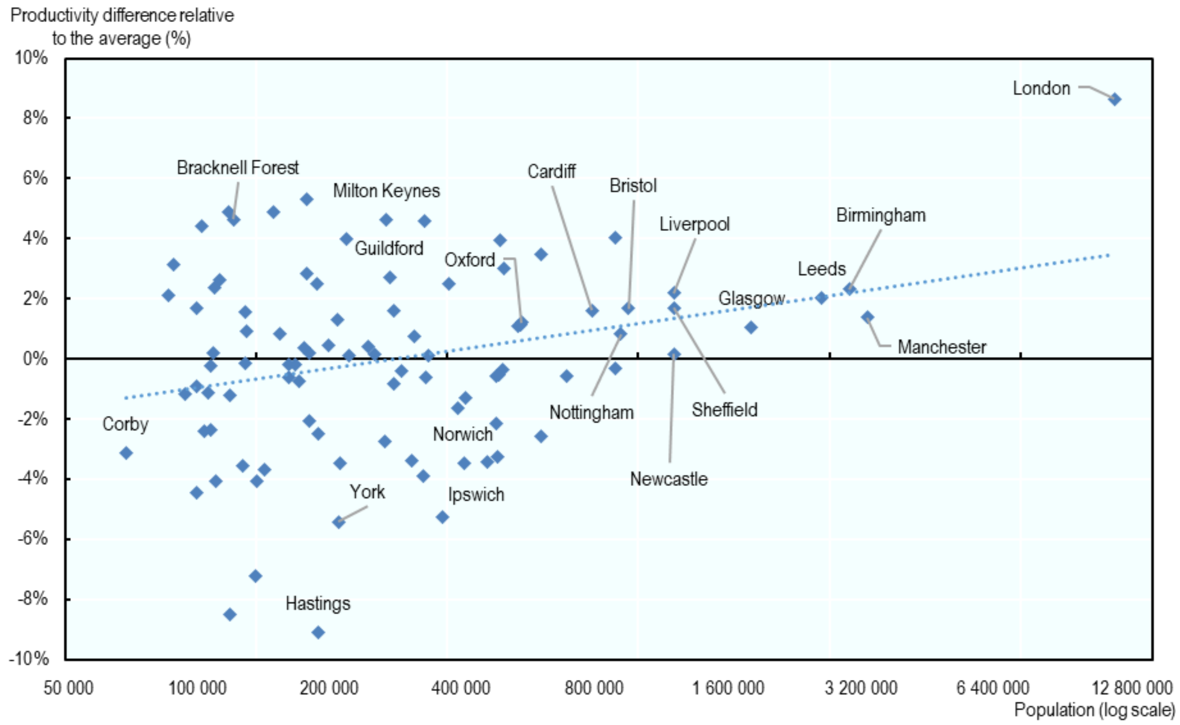
Second-step regressions

The city-year fixed effects ($\widehat{\gamma_{at}}$) obtained in the first-step capture productivity differential across cities, net of (observable and unobservable) skill differences and the industry structure of the local economy. Figure 2 plots the city fixed-effects estimated in column (4) against city population size.[6] Notable geographic differences in earnings exist even for observationally equivalent workers. For instance, a worker in London earns around 12 percent more than a worker with the same observable characteristics in Corby — the smallest city in the sample. The largest earning differential of 17,7 percent is found between workers in London and Hastings.

[6] For visual simplicity, the figure plots estimated fixed effects for 2018.

Figure 2. Agglomeration economies in Great Britain (2018)

Productivity differences (net of the workforce and sectoral composition, 2018) and population size (2018)



Note: Population (log scale) on the horizontal axis, the vertical axis plots city productivity, estimated by applying individual wage regressions to ASHE microdata to control for workforce and industry composition of cities. Log hourly wages/earnings are regressed on gender (dummy), age, age squared, education (dummies) occupation (dummies), full-time (dummy), specialisation index, individual fixed effects and city-year dummies; the coefficients of the latter are taken to denote productivity differentials. The analysis is conducted at the Functional Urban Area level.
Source: OECD calculations based on the UK Annual Survey of Hours and Earnings (ASHE) microdata.

Table 3 presents the second-step estimation results of equation (2) where estimated city-year fixed effects ($\widehat{\gamma_{at}}$) are used as the dependent variable and regressed on time-varying city characteristics (Qat). Columns 1 of Table 3 show that the population has an elasticity of 0.0091. This means that doubling the city population in a UK city increases the average productivity roughly by 1 percent. This elasticity is identical to what has been found for the UK (D'Costa and Overman (2014[23]); Ahrend et al. (2017[24])).

To provide estimates comparable to the literature, the other columns present density of employment instead of the total local population as main variable of interest. Column 2 shows that elasticity of density is 0.0051. While density captures partially the positive gains associated with denser cities, it does not capture gains that arise from the size of the city. Use of both density and surface area is helpful as it allows disentangling the source of agglomeration benefits. For instance, the coefficient of density gives the elasticity of city productivity with respect to employment density, holding constant the surface area coverage by a city. This allows capturing the gains associated with a thicker labour market. The coefficient of land area captures the impact of an expansion of city limits while density remains constant. A larger city is likely to have more non-market interactions among agents than a smaller area as it is more populated. To capture these effects, the surface area is added to Column 3. Controlling for surface area (or the extent of the city) doubles the estimated elasticity to 0.01, which is similar to elasticity obtained in Column 1, using population.

Column 4 accounts for human capital spillovers by including the share of university graduates, which shows a positive relationship with productivity. The estimated elasticity indicates that a 10-percentage point increase in the share of university graduates is associated with a 1.7 percent increase in productivity of the overall workforce, an effect that is statistically significant. It is important to note that this number captures only the positive spillovers associated with having an educated workforce as private returns to education are already accounted for in the first-step. Column 5 includes the Herfindahl Index of industry concentration which is positive yet statistically insignificant which is common in the literature (Combes and Gobillon, 2015[3]). Road access performance is added in the final column. Empirically, the analysis shows that a one standard deviation 10-percentage point (or around one standard deviation) increase in the road accessibility performance of a city increases the average productivity by 1.2 percent.

Table 3. Local determinants of productivity

Second-step regression: 2000-2018

	(1)	(2)	(3)	(4)	(5)	(6)
VARIABLES	Year-Area FE	Year-Area FE	Year-Area FE	Year-Area FE	Year-Area FE	Year-Area FE
Log Density		0.0051**	0.0118***	0.0106***	0.0141***	0.0131***
		(0.0021)	(0.0027)	(0.0026)	(0.0033)	(0.0031)
Log Area			0.0074***	0.0062**	0.0095***	0.0091***
			(0.0024)	(0.0024)	(0.0034)	(0.0032)
Share of graduates in Employment				0.0017**	0.0019***	0.0017***
				(0.0007)	(0.0006)	(0.0006)
Herfindahl Index					0.0716	0.0765
					(0.056)	(0.060)
Road Access						0.00122***
						(0.0003)
Log Population	0.00919**					
	(0.0033)					
Observations	1767	1767	1767	1767	1767	1767
R-squared	0.9484	0.9594	0.9625	0.9634	0.9639	0.9854
Year Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes

Note: Table reports OLS estimates where the dependent variable is the area-year fixed effects estimated in the first-step regression. The dependent variable is regressed on a set of local characteristics. Regressions are weighted by total employment in the period. Standard errors are clustered at area-level. *** p<0.01, ** p<0.05, * p<0.1
Source: OECD calculations based on the UK Annual Survey of Hours and Earnings (ASHE) microdata.

The Great Recession: Any changes in agglomeration economies?

Since the onset of the 2007–08 global financial crisis, labour productivity growth in the United Kingdom has been exceptionally weak. In 2018, the productivity level was just 2.5 percent higher than in 2008 and remained well below the level implied by a simple continuation of its pre-crisis trend. This weak performance has been called the ‘Productivity Puzzle’ and has caught the interest of both academics and policy-makers (Haldane et al., 2017[25]). Despite various explanations provided, no consensus exists regarding the causes of the productivity slowdown.

The profound impact of the financial crisis has prompted numerous studies by economists of its causes and consequences for individuals, their families, communities, and the general economy (Kalleberg and Von Wachter, 2017[26]). Given the significant changes observed across the economy, it is possible that changes in the economy may have also affected the agglomeration economies in Great Britain.

To investigate whether the relationship between city size and productivity has experienced a structural break during the crisis, the sample is broken into two periods 2000 to 2008 and 2008 to 2018 and elasticities are estimated for both periods separately. Table 4 presents the results for both periods.[7] Estimated elasticities for density remain identical in both periods indicating that agglomeration effects have not changed in the aftermath of the crisis.

Table 4. Local determinants of productivity: Pre-crisis vs. post-crisis

Second-step regression results: 2000-2018 vs. 2008-2018

	2000-2008				2008-2018			
	1	2	3	4	5	6	7	8
VARIABLES	Year-Area FE	Year-Area FE	Year-Area FE	Year-Area FE	Year-Area FE	Year-Area FE	Year-Area FE	Year-Area FE
Log Density	0.0051**	0.0118***	0.0106***	0.0141***	0.0049**	0.0108***	0.0095***	0.0116***
	(0.0021)	(0.0027)	(0.0026)	(0.0033)	(0.0022)	(0.0027)	(0.0026)	(0.0031)
Log Area		0.0074***	0.0062**	0.0095***		0.0059***	0.0052**	0.0075**
		(0.0024)	(0.0024)	(0.0034)		(0.0021)	(0.0021)	(0.0029)
Share of graduates in Employment			0.0017**	0.0019***			0.0006	0.0008*
			(0.0007)	(0.0006)			(0.0005)	(0.0005)
Herfindahl Index				0.0716				0.0774
				(0.056)				(0.0756)
Observations	837	837	837	837	1,023	1,023	1,023	1,023
R-squared	0.9594	0.9625	0.9634	0.9639	0.9602	0.9632	0.9635	0.964
Year Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes

Note: Table reports OLS estimates where the dependent variable is the area-year fixed effects estimated in the first-step regression. The dependent variable is regressed on a set of local characteristics. Regressions are weighted by total employment in the period. Standard errors are clustered at area-level. *** p<0.01, ** p<0.05, * p<0.1
Source: OECD calculations based on the UK Annual Survey of Hours and Earnings (ASHE) microdata.

[7] Results including road access also hold. They can be provided if requested.

Concluding remarks

This paper estimates the productivity differentials of functionally defined cities – FUAs – across Great Britain and studies the determinants of urban productivity. Administrative microdata is used in a two-step econometric approach to analyse pure productivity advantages that arise at the city level while accounting for the potential sorting of more productive individuals into certain cities which is the most important bias in the estimation.

Results indicate a positive effect of density on productivity in Great Britain. The estimated elasticity of 1 percent is at the lower end of the estimates found in the literature suggesting the weak presence of agglomeration economies in the Great Britain context. Furthermore, the estimates show that the relationship has not changed since the Great Recession.

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Annex A. Technical Appendix

Appendix Section: Education variable

The variable education was constructed by regressing year of education on date of birth and date of birth squared by two digit occupation code. Specifically the years of schooling are regressed on the year of birth and year of birth square separately for each four-digit occupation using the LFS data from 2000 and 2018. The estimated coefficients for each occupation is then used to simulate years of schooling for all individuals based on their year of birth and occupation.

This generated 4 different categories of education levels:

1. Secondary Education (less than and equal to 10 years of full time education)
2. Upper Secondary Education (greater than 10 and equal12 years of education)
3. University Education (greater than 12 and less than 15 years of full time education)
4. Postgraduate Education (More than 15 years of full time education)

Table A A.1. Summary statistics for first-step regressions

Variable	Mean	Standard Deviation
Earnings	12.5	10.59
Male	0.51	0.5
Age	42.39	10.44
Lower secondary education	0.06	0.23
Upper secondary education	0.26	0.44
University education	0.41	0.49
Postgraduate	0.27	0.45
Full time	0.78	0.41
Public sector	0.35	0.48
Collective agreement	0.53	0.5
Specialization	0.19	0.09
Industry		
Agriculture, forestry and fishing	0.004	0.007
Energy and water	0.02	0.15
Extraction of mineral and ores other than fuel	0.07	0.26
Metal goods, engineering and vehicles	0.04	0.19
Other Manufacturing industries	0.04	0.2
Construction	0.17	0.38
Distribution, hotels and catering	0.13	0.33
Transport and communication	0.21	0.4
Banking, finance, Insurance, business services and leasing	0.28	0.45
Other services	0.04	0.19
Occupation		
Managers and senior officials	0.13	0.34
Professional occupations	0.15	0.36
Professional and technical occupations	0.15	0.35
Administrative and secretarial occupations	0.17	0.38
Skilled trades occupation	0.07	0.26
Personal service occupations	0.08	0.26
Sales and customer service occupations	0.07	0.26
Process, plant and machine operatives	0.07	0.26
Elementary occupations	0.11	0.31

Note: Table presents summary statistics for individual analysis. Number of observations 1,988,855
Source: OECD calculations based on the UK Annual Survey of Hours and Earnings (ASHE) microdata.

Table A A.2. Summary statistics for second-step regressions

Variable	Mean	Standard Deviation
Population	515378.23	1206377.39
Area	916.289	1293.853
Share of Graduates	0.221	0.12
Herfindahl	0.061	0.055
Road Access Performance	87.949	11.00

Note: Table presents summary statistics for individual analysis. Number of observations 1767.
Source: OECD calculations based on the UK Annual Survey of Hours and Earnings (ASHE) microdata.