Too close for comfort? Micro-geography of agglomeration economies in the United Kingdom

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Too close for comfort? Microgeography of agglomeration economies in the United Kingdom

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Abstract

The issue of whether firm productivity is affected by agglomeration externalities is a longstanding area of research. However, the appropriate geographical level to better detect the effects of agglomeration economies and at which level these externalities work is still unclear. Using detailed firm-level longitudinal data on 4927 manufacturing firms in the United Kingdom over the period 2008–2016, we investigate the relation between the microgeography of external agglomeration economies and firm productivity. We compare different geographical levels: city-wide and narrowly defined neighborhoods around a firm. Results from a multilevel (mixed-effect) model show that urbanization externalities play a role at a higher level of geographical aggregation, such as the city, whereas localization externalities operate at a finer level, within the city and in a closer neighborhood to the firm. Failing to control for more granular levels of geography results in confounding the two types of externalities. We also provide novel evidence that these externalities vary across firm (such as age, size, and productivity) and location (such as population density) characteristics.

KEYWORDS

agglomeration economies, heterogeneity, localization, microgeography, mixed-effect models, productivity, urbanization

1 | INTRODUCTION

External agglomeration economies, generated by the geographical concentration of economic activities, may increase the competitiveness of a specific area and contribute to the productivity of firms located there (Barca et al., 2012; Martin & Ottaviano, 2001; McCann & Van Oort, 2009; Menghinello et al., 2010; Rodríguez-Pose, 2011). While the extent and the role played by external agglomeration economies on location, industry and firm productivity are well-established facts (Beaudry & Schiffauerova, 2009; Quigley, 1998; Rosenthal & Strange, 2004), there is no consensus on the most appropriate geographical unit of analysis to detect the effects of such agglomeration economies. Research has documented that *urbanization* and *localization* externalities may coexist and some recent evidence points to the possibility that they may operate at different geographical scales (Andersson et al., 2019).

Following this insight, we investigate the microgeography of external (*urbanization* and *localization*) agglomeration effects on firm productivity. In particular, we simultaneously analyze different levels of relatively fine geographical disaggregation, namely the city-wide level and narrowly defined neighborhoods around a firm. To do this, this study carries out a multilevel (mixed-effect) empirical analysis on detailed firm-level data of 4927 manufacturing firms in the United Kingdom covering the period 2008–2016. A multilevel approach allows to take into account the association of firm productivity with both the individual firm-specific characteristics and the contextual (location) characteristics. In addition, it allows to flexibly model the heterogeneity in the net benefits each firm receives from agglomeration economies, across geographical levels, and by characteristics of firms and locations. Our findings show that both urbanization and localization are positively associated with firm productivity, but these forces operate at different geographical scales. Indeed, urbanization economies play a role at a higher spatial level of analysis, whereas localization externalities operate in a closer neighborhood to the firm. This suggests that there is no such thing as being too close for comfort when it comes to Marshallian externalities, as firms benefit from being located in a very close proximity to other companies operating in the same industry. Failing to control for these close neighborhood effects may result in finding localization at a (relatively aggregated) higher level. On the contrary, positive urbanization externalities appear only at the city-wide level and are negative at the neighborhood level, suggesting that being too close to other firms does not help exploit such benefits.

Furthermore, beyond a such average effect, we predict a firm-specific elasticity of productivity to agglomeration economies and investigate whether these differ systematically across firms. On the one hand, we support the idea that high population density may negatively correlate with specialization externalities, due to congestion effect, and that urbanization externalities need a larger geography. If city-regions are too small they do not generate enough potential for urbanization externalities (Cainelli et al., 2015). On the one hand, we show that different firms benefit from agglomerations in a different way. In particular, older and less productive firms seem to benefit more from specialization externalities occurring at a narrow geographical level. This is consistent with the idea that this type of benefit is mainly cost-reducing and suits established firms, which are not exploring new ways of doing business (Duranton & Puga, 2001). Furthermore, the most productive firms may shy away from highly agglomerated neighborhoods, to protect their competitive advantage (Shaver & Flyer, 2000). Instead, urbanization externalities in a larger geography seem to benefit younger firms relatively more, as well as larger and more productive firms. This is in line with the idea of the city as a diversified environment that can nurture younger firms allowing them to experiment and learn about the development of new ideas, products, and production processes (Duranton & Puga, 2001). At the same time, to fully benefit from cross-fertilization of ideas and innovation processes, firms need to bear the sunk costs to develop abilities needed to absorb and take advantage of such forms of urbanization externalities (Alcácer & Chung, 2007). These arguments are also consistent with the fact that larger and more productive firms benefit more from urbanization externalities at a city-wide level.

Our paper contributes to the literature in three main ways. First, we provide additional evidence on the role of agglomeration economies on firm productivity, moving toward a microgeographical approach (Andersson et al., 2019). Second, by exploiting a property of mixed-effect models (Alcácer et al., 2018; Castellani & Lavoratori, 2020), we also contribute to the debate on the factors that moderate the benefits that firms achieve from locating in highly agglomerated areas. Lastly, we aim at contributing to the recent call for subnational and sub-regional analyses to overcome country boundaries and investigate location phenomena at extremely fine-grained geographical scales (M. Feldman, 2014; Mudambi et al., 2018) to capture within-country heterogeneity (Ottaviano, 2011) and zoom in "to a much smaller scale to get a true picture of locational advantage" (Mudambi et al., 2018, p. 936).

The remainder of the paper is organized as follows. The next section presents the related literature on the microgeography of external agglomeration economies and firm productivity. Section 3 describes the data. Section 4 presents the empirical strategy. Section 5 illustrates the findings. Section 6 concludes.

2 | RELATED LITERATURE: TOWARD THE MICROGEOGRAPHY OF AGGLOMERATION ECONOMIES

Agglomeration economies are the positive externalities generated from the geographical proximity and concentration of firms in a given location. Two main different types of agglomeration economies exist (Glaeser et al., 1992). On one hand, the geographical concentration of firms from the same industry generates "localization" or "specialization" externalities (Marshall, 1890), later formalized in the so-called Marshall–Arrow–Romer (MAR) framework (Arrow, 1962; Romer, 1986). These externalities arise thanks to the local formation of a specialized labor market created by the industry demand and specialized suppliers, as well as the emergence of industry-specific knowledge spillovers, also among competitors. The intra-industry interaction and transmission of knowledge across economic agents positively affect the innovation process and firm performance.

On the other, the concentration in a location of firms from different industries may generate "urbanization" or "diversification" externalities. The diversity of industries in a geographical location promotes externalities, innovation activity, and economic growth. This is based on the idea that the most important sources of knowledge spillovers are external to the industry in which the firm operate, and the knowledge arises more between—rather than within—industries (Jacobs, 1969). Besides the benefits highlighted above, agglomeration of economic activities may result in negative externalities, mainly in the form of congestion costs, which increase the costs of production factors, and competition effects, which may crowd out weaker firms and discourage industry leaders to locate in highly agglomerated locations to minimize knowledge leakages (Krugman, 1991; Richardson, 1995; Shaver & Flyer, 2000).

A substantial body of empirical literature has investigated the extent of agglomeration economies and their industrial scope, leading to a lively debate about localization versus urbanization externalities (Beaudry & Schiffauerova, 2009; Combes & Gobillon, 2015; Ellison et al., 2010; Faggio et al., 2017; Puga, 2010; Rosenthal & Strange, 2004). Other studies investigate the role of agglomeration economies on performance, looking at the impact of urbanization and localization externalities on several measures of performance, that is, economic growth, productivity, and innovation (Ciccone & Hall, 1996; M. P. Feldman & Audretsch, 1999; Glaeser et al., 1992; J. V. Henderson, 2003; V. Henderson et al., 1995; Rosenthal & Strange, 2003). These studies are conducted with both an aggregated (regional level) and firm-level approach, where firm-level analyses dominate in studies about innovative and export performance (Beaudry & Schiffauerova, 2009; Malmberg et al., 2000).

Another relevant issue raised in this field of research, concerns the actual geographical units of analysis to detect agglomeration economies, due to their strong spatial decay effects (Cainelli & Ganau, 2018).

Earlier studies adopted more aggregated units of analysis (national, state, and regional level) but more recent studies moved to a finer spatial unit (such as the city level), highlighting that agglomeration effects present a strong geographical decay. Combes and Gobillon (2015) find that agglomeration effects fade within 100 km, and a recent survey shows that in 80% of empirical studies on agglomeration effects, the threshold is within 80 km, and in 60% of cases the threshold is within 20 km (Drucker, 2012). Rosenthal and Strange (2003) analyze the effect of agglomeration economies on the birth of new establishments and their new employment using data in six different industries in the United States, at the ZIP-code level. They find that localization economies (measured by the employment in their own industry) are more important than urbanization externalities (employment in other industries) and that the former rapidly decline with the increase of distance. Instead, urbanization economies present a trade-off between the benefits of being located close to high-populated areas and the related congestion costs. Their results suggest that agglomerations need to be studied at a more granular level, while previous studies have considered agglomeration economies as a "club goods that operate at a metropolitan scale" (Rosenthal & Strange, 2003, p. 377).

Indeed, as Arzagli and Henderson (2008) underline, in a study on the birth of firms in the advertising agency industry in Manhattan, the proximity of other advertising agencies has an effect on the location choices of new firms, presenting a strong spatial decay effect, due to the importance of information spillovers and sharing in an industry with a high level of tacit knowledge and strong localization of the nearest neighbors. Personal interactions and "human capital spillovers" can rapidly decay with the increase of distance among operators, especially in non-routine activities (Larsson, 2014, 2016). In the same direction, Van Soest et al. (2006) examine the role of agglomeration economies in employment growth during the period 1988–1997 in the province of South-Holland in the Netherlands, using data at postal code level (where each zip code covers an area of less than 6 km^2). They find that agglomeration economies in one location do not have any significant effect on the employment growth in the near locations, confirming this idea that agglomeration externalities operate on a spatial scale smaller than the city. A subsequent study based in the Netherlands, reveals that agglomerations have a positive and significant effect on wages within a distance of 5–10 km, becoming insignificant after 40 km or in a too short distance (smaller than 5 km), potentially because agglomeration economies in a smaller area might affect other factors than wages (Verstraten et al., 2018).

Yet, the majority of these previous works investigates the spatial decay phenomenon considering agglomeration forces as in competition with each other, some even asking specifically the question of whether Marshall or Jacobs was right (Beaudry & Schiffauerova, 2009; Caragliu et al., 2016). However, localization and urbanization externalities do not necessarily "compete," they may "coexist" in the same geographical areas, because the combination of these economies may contribute to firm growth, but in different ways. Duranton and Puga (2001) underline that both diversified and specialized cities are important in an urban economic system, but in different stages of the product life cycle: in the early stages, firms need a more diversified environment to develop a new product, a city as a "nursery" for firms; when the product and process are well-developed, firms need a more specialized city to conduct mass production and reduce production costs. M. P. Feldman and Audretsch (1999) highlight that both diversity and localization of economic activity in a city promote innovative output, but diversity of complementary industries—sharing a common science base—creates greater firms' returns from R&D activities, focusing the analysis in the US cities, or when these share a technological closeness (Combes, 2000). In a large sample of Italian manufacturing firms, Cainelli and Lupi (2010) find that localization effects are positive within 2 km, but decreasing over distance. On the contrary, diversification effects are negative up to 10 km, but positive between 10 and 30 km. Similarly, Cainelli and Ganau (2018) find that diversification-type forces have negative effects on productivity growth at short distances, while there are positive effects at longer distances. Instead, positive localization economies increase with distance, but only when the characteristics of neighboring firms are accounted for. More recently, Andersson et al. (2019) investigate sub-city scales for testing the attenuation of agglomeration effects in Sweden. They highlight that localization externalities operate in a closer neighborhood (in 1 km^2), while urbanization externalities operate both at the local neighborhood level and city level, especially for high-tech and knowledge-intensive industries that may benefit from the "cross-fertilization" between industries, to generate new ideas and innovation. This result is in line with the study conducted by Rammer et al. (2020) in Berlin, showing that innovative firms benefit from a close proximity (up to 250 m) to other firms and start-ups operating in the same sector, due to the key role played by knowledge spillovers.

Based on the discussion of previous literature, we gather that a fine level of geographical disaggregation may be more appropriate to better detect agglomeration economies effects. At the same time, different types of externalities are not mutually exclusive, they may coexist in the same local environment rather than compete, but at the same time they may operate at different spatial scales.

On the one hand, localization externalities operate through mechanisms such as specialized labor pool, local knowledge, and inputs, that require both economic—in the industrial scope—and geographical proximity to reduce costs of search (also in the labor market) and knowledge transfers, as well as transaction costs. People and ideas (as well as capital and goods) tend to be "sticky" in an area (Barca et al., 2012). Proximity can facilitate interactions and communication, coordination and monitoring, exchange of information and knowledge, as well as lead trust across economic parties, crucial factors in the relations with clients and suppliers (Schmitt & Van Biesebroeck, 2013). This transfer can be facilitated also thanks to the presence of common social and institutional infrastructures, as well as networks, within relatively small areas (Rodríguez-Pose & Crescenzi, 2008). On the other hand, urbanization externalities derive from industry variety that can increase possibilities for cross-fertilization of existing ideas and a broader diversification of skills and knowledge, to endorse innovation, new ideas, processes, and products. Moreover, a diversified area is less vulnerable to lock-in effects and more able to adjust to exogenous changes (Beaudry & Schiffauerova, 2009). At the same time, the presence of many specialized clusters and the frequent interaction among multidisciplinary individuals can determine urbanization economies and promote technological innovation (Desrochers, 2001). Regions with higher population (or employment) density are also seen as more diversified (Beaudry & Schiffauerova, 2009). We submit that this diversified knowledge can be better achieved over a larger geographical space.

Based on the above discussion of the literature, four empirical issues emerge as open questions in the relation between agglomeration economies and firm productivity: (1) whether either *localization* or *urbanization* economies are positively associated with the productivity of firms embedded in a location, or rather both matter; (2) which appropriate spatial level of analysis can help us to better investigate and detect the relation between agglomeration economies and productivity; (3) whether *localization* and *urbanization* externalities "coexist" in the same geographical area, but operating at different spatial scales; finally (4) whether this relation is homogeneous, or rather, as some studies suggest, several moderating factors can affect the firm individual benefits from agglomeration economies, resulting in a heterogeneous response across firms and locations.

3 | DATA

Our empirical analysis relies on detailed firm-level longitudinal data over the period 2008–2016 on a sample of about 10 thousand manufacturing firms active in the United Kingdom[1] from Bureau van Dijk's *Fame* database[2] and with no missing values for the relevant firm-level information. Exploiting the information on the number of subsidiaries of each firm, we identify 4927 firms with zero (national or foreign) subsidiaries, thus we focus on this sample in our analysis, to avoid spurious effects due to the presence of headquarters or other administrative units. However, we retain information on the whole sample of UK firms (including those operating in the service sectors) to compute our agglomeration measures.

We obtain economic and financial data and information on the sector of activity and the location where firms are established. We define large firms as those with more the 250 employees, medium-sized firms with 50–250 employees, and small firms with less than 50 employees, following the Eurostat classification. Our sample consists of 31.8% of firms classified as small, 58.5% as medium, and 9.7% as large.

We identify the exact location of each firm relying on postcode information. In the United Kingdom, each postcode generally represents a street or part of a street—depending on the amount of business and private mails

[1]Northern Ireland is excluded from the study because of the potential bias due to the fact that we cannot control directly for contiguity effects generated by close firms, but located in the Republic of Ireland. However, as a further robustness check we include the manufacturing firms located in the region.

[2]NACE Rev. 2 industries 10-33. Considering also the service industries, the overall database covers over 100 thousand firms.

received by an address. Thus, the postcode can identify the location of a company quite precisely. The UK postcode system is a sophisticated structure of postal geographical boundaries developed and managed by Royal Mail, along with the ONS and other organizations that provide several statistics due to the relevance of such unit of analysis for several purposes. In detail each postcode is an alphanumeric code, from six to eight character (including a space) long. Each postcode is divided into two parts (separated by a single space): the *outward* and *inward* code. The *outward* code includes the postcode area and the postcode district, respectively. The *inward* code includes the postcode sector and the postcode unit, respectively. Besides using the postcode to geo-reference each firm, in this study we use the information provided by the postcode area, which is either one or two characters long and is all letters. The postcode area normally defines a city with its surrounding areas, but it can occasionally define boroughs within a city (such as in the case of London), or larger areas (such as "IV" (Inverness) which covers the Northern part of Scotland).

Figure 1 graphically shows the geographical distribution of postcode areas and manufacturing firms in our sample across the country.

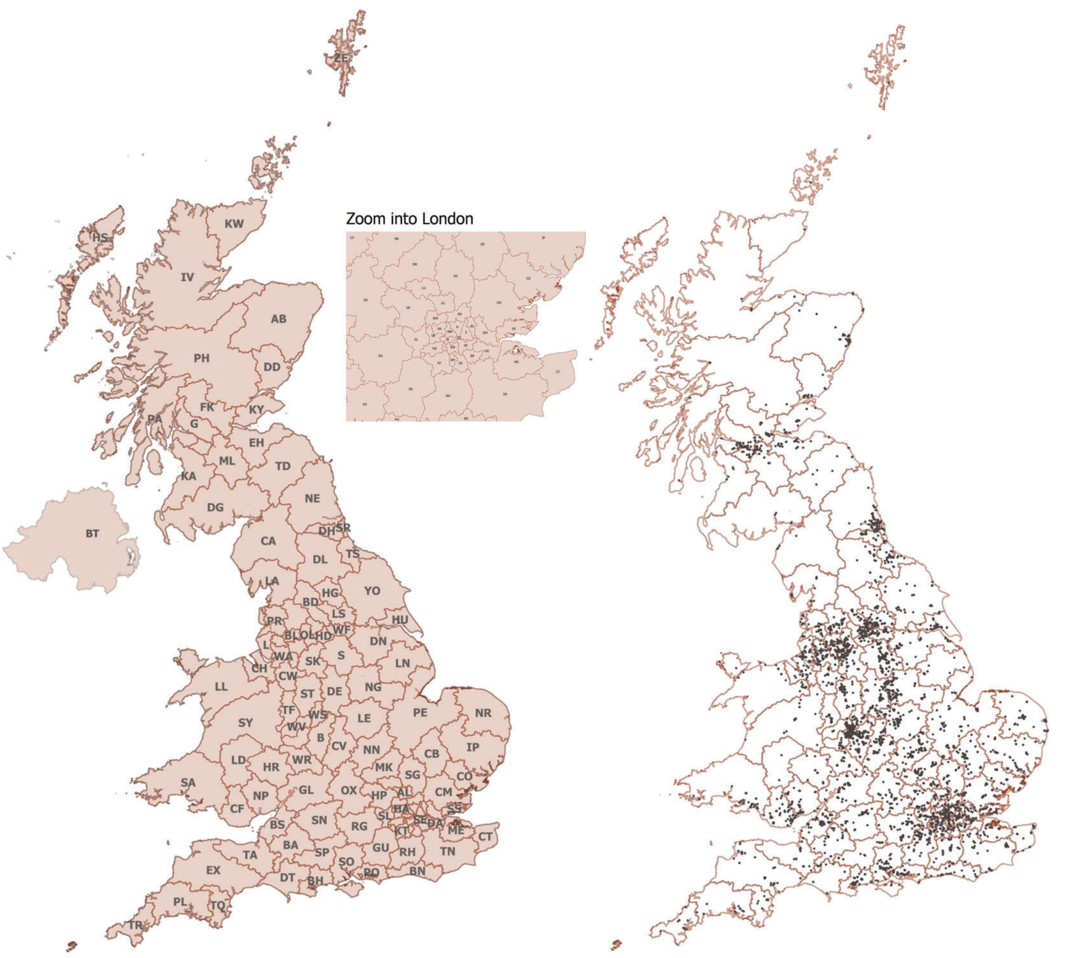

FIGURE 1 Geographical distribution of postcode areas and manufacturing firms in the United Kingdom. *Source*: Authors' elaboration from Fame database [Color figure can be viewed at wileyonlinelibrary.com]

There are 120 postcode areas in the United Kingdom. In our data, we have at least one sample firm in 118[3] postcode areas, with an average (median) area of 1769 (1380) Km,[24] with an average population of 710,864 residents.[5] We will use the postcode areas as an indication of city-wide boundaries.

4 | EMPIRICAL STRATEGY

4.1 | Methodology

Our dependent variable is the firm productivity, which is modeled as a function of both individual firm characteristics and the social, institutional, and economic environment in which firms are embedded. The performance of firms established in the same location may be strongly correlated because these share a set of unobserved factors such as similar information, formal and informal institutions, same services and infrastructures. For these reasons, we need to account for the correlation in the economic outcomes between firms and the economic areas in which these are located, because firms can be considered as nested within the location in which they operate.

Multilevel linear (also known as hierarchical, random-effect, or mixed-effect) models allow to simultaneously model firm and location variables, controlling for the spatial dependence due to the nested structure of the data and correcting standard errors measurements (Hox, 2002). A multilevel analysis allows to study the variance of the outcome at each level, measuring the unobserved group-level heterogeneity, but maintaining the firm as the unit of analysis (Hofmann, 1997). In our case we have three levels. Due to the longitudinal nature of the data, the first level of the hierarchy is the different measurement occasions over time t of the dependent variable for each firm over the 2008–2016 period, representing our observations. The literature on this class of models suggests treating time as a continuous variable (Hedeker & Gibbons, 2006). Thus, observations are nested within firms—the second level of the structure, lastly firms are clustered in the same location (i.e., postcode area) which represents the third level of the structure.

The multilevel mixed-effect models can be seen as an extension of the random effect (RE) panel data models when there are several levels in the data, thus we can allow for the influence of each level on the outcome, while RE does not estimate separate relationships at any level of the hierarchy. In so doing, the unexplained residual variance will be decomposed into the variance at higher levels among firms and lower-level variance within firms, but among occasions (years). This results in having a residual term at each level, where the higher-level residuals are the so-called random effect (Bell & Jones, 2015; Bell et al., 2019).

Considering a simple linear regression model formalized as follows:

$$Y_{ijt} = \beta_0 + \beta_1 X_{1ijt} + \beta_2 X_{2it} + \delta Year_t + \varepsilon_{ijt}, \tag{1}$$

where Y_{ijt} is the dependent variable, X_{1ijt} and X_{2it} are a set of firm-location and firm characteristics. If we allow for differential intercepts for higher levels, the randomness in the intercept is introduced (β_0) at all relevant levels (i.e., postcode area and firm), whereas β_1,β_2, and δ are fixed coefficients equal to all firms. The coefficient β_0 can be now expressed as

$$\beta_0 = \gamma_{000} + u_{0j0} + u_{ij0}, \tag{2}$$

[3]No manufacturing firms are located in the “HS” (Outer Hebrides) area, which corresponds to the archipelago in the West coast of Scotland. As for Northern Ireland, there are 134 manufacturing single-plant firms in our sample located in the “BT” (Belfast) postcode area.

[4]All the average land size and distribution statistics at the postcode area are computed by the authors using the information included in the shapefiles released by Pope (2017, for more details see https://datashare.is.ed.ac.uk/handle/10283/2597), elaborated using QGIS software.

[5]Data on resident population at the postcode area level are from the 2011 Census provided by the ONS and the Official Labour Market Statistics (Nomis) for England and Wales (for additional details, see https://www.nomisweb.co.uk/census/2011/qs417ew), and by the Information Services Division for Scotland (for additional details, see https://www.isdscotland.org/Products-and-Services/GPD-Support/Population/Census/).

where γ_{000} is the overall mean, and u_{0j0} and u_{ij0} are the random part of the model consisting of higher-level residuals, in other words u_{0j0} is the distance from the sample mean ascribed to the area level j, and u_{ij0} to the firm-level group i.

So far, the model has assumed homogeneous effects associated with the predictors, but this can hide heterogeneous behaviors across firms. A step further consists in explicitly modeling such heterogeneity, allowing for the randomness not only in the intercept but also in the slope of some (or all) predictors, and estimating firm-specific parameters that capture the individual response to agglomeration economies. For example, the variable X_{1ijt} in (1) can be set as random at the firm level, thus formally the model can be extended as follows:

$$Y_{ijt} = \gamma_{000} + u_{0j0} + u_{ij0} + \beta_{1i}X_{1ijt} + \beta_2 X_{2it} + \delta Year_t + \varepsilon_{ijt}, \tag{3}$$

Where

$$\beta_{1i}X_{1ijt} = \gamma_{10}X_{1ijt} + u_{1i}X_{1ijt}, \tag{4}$$

namely, γ_{10} is the overall mean slope and u_{1i} is the slope deviation of firm i for the variable X_{1ijt}. Furthermore, such modeling allows to predict the firm-specific random component u_{1i} and investigate which factors can explain its variation across firms.

However, to test the robustness and ensure comparability of our results, we also estimate a firm fixed effect (FE) model, using a within-group estimator, which is more widely used in the literature.

4.2 | Model specification

4.2.1 | Dependent variable

Our dependent variable is the total factor productivity (TFP) of firm i in year t. TFP is computed as the residual of a Cobb–Douglas value-added production function, where labor is measured as number of employees, and capital stock is measured in terms of fixed assets. We derive all this information from Fame database. We compute the TFP using several techniques[6], namely OLS, OLS augmented with firm size, year, industry and regional dummies (OLS_D), firm FE estimator, and using the methods proposed by Levinsohn and Petrin (2003) (LP) and Ackerberg et al. (2015).[7] We find a high correlation between TFP estimates, between 0.6 and 0.97[8], in line with previous literature (Van Beveren, 2012; Van Biesebroeck, 2007). As our baseline estimator we select the LP[9], which employs a two-stage estimation proxying the unobserved productivity shocks by using the intermediate inputs, given that it is considered a relatively robust estimation method and LP are highly correlated with all the other methods.

4.2.2 | External agglomeration variables

Our main explanatory variables are measures of external agglomeration economies in the focal location, based on the number of employees. Agglomeration variables are normally computed based on the number of establishments or employees. Previous literature has argued for the latter, given that the employment count allows to better account for scale effects compared with the establishment count (Arzagli & Henderson, 2008; Martin et al., 2011).

[6]For a recent literature review, see Ackerberg et al. (2015).

[7]We cannot estimate the TFP using Olley and Pakes (1996), because we do not have the information on firm exit.

[8]Table with correlations between TFP estimate is available under request to the authors.

[9]We estimate the TFP-LP using the `levpet` package in Stata 14 and 16.

Following recent contributions in the field (Andersson et al., 2019), we create different spatial layers for measuring agglomerations adopting a microgeographical approach. In particular, we adopt a grid scheme to identify (1) the *neighborhood* of the company, as the 1 × 1 km square where the centroid is the focal company, corresponding to the finest geographical level; (2) the *within-city* level, as the 3 × 3 km square around the firm, corresponding to the first-order contiguous area around the 1 × 1 km square neighborhood. The idea is to create squares of different sizes geocoded around the actual geographical coordinates of a company. This method can reduce endogeneity issues of alternative geographical boundaries, since the grid can be seen as fixed-determined and exogenous to the economic activities in the area. Figure 2 shows an example of the square grid system, created using QGIS software. Finally, we use a layer capturing (3) the *city-wide* level, relying on the postcode area delineations. This is our most aggregated geographical unit of analysis. As an additional robustness check we create the agglomeration measures geo-coding each postcode into its Nomenclature of Units for Territorial Statistics (NUTS-3) area (Eurostat, 2018) in order to test the sensitivity of the aggregated administrative unit adopted.

Each of the following agglomeration variables is computed at the relevant geographical units, that is the neighborhood or city-wide.

Localization (or specialization) economies

To capture the externalities associated with specialization economies (Marshallian agglomeration economies), we compute—for each firm *i*—the number of employees working for other firms in the same industry *s* and in the same location *l*. More formally,

$$Localization_{slt} = \ln\ (No.\ Empl_{slt} - No.\ Empl_{islt} + 1).$$

Urbanization economies

To capture the externalities associated with Jacobian agglomeration economies we use two measures, namely:

(i) *Urbanization (Density of economic activity)*: we compute the number of employees in other industries different from the industry in which the firm *i* operates, in the area *l*, where the plant *i* is located. Formally,

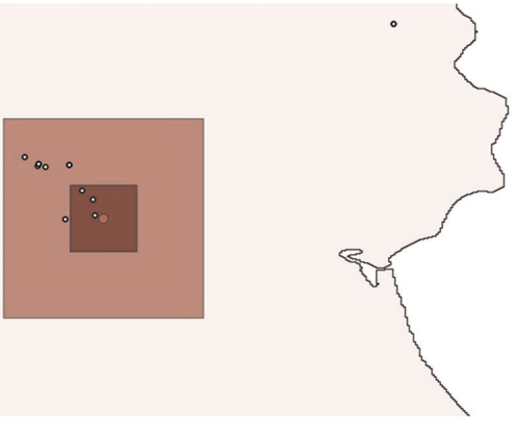

FIGURE 2 Example of square grid around focal firms. The red (and bigger) dot is a focal manufacturing firm—centroid of the square, that is, 1 × 1 (darker) and 3 × 3 (lighter) km squares. White dots correspond to other manufacturing or service firms. Each square can be considered as firm-specific. *Source*: Authors' elaboration from Fame, using QGIS software [Color figure can be viewed at wileyonlinelibrary.com]

$$Urbanization_{lt} = \ln\ (No.\ Empl_{lt} - No.\ Empl_{slt} + 1).$$

(ii) *Industrial diversity*. We compute a measure of industrial diversity faced by firm *i* operating in industry *s* in the area *l* at time *t*, more formally, as

$$Industrial\ \ Diversity_{lst} = 1/H_{lst},$$

where H_{lst} is defined as follows:

$$H_{lst} = \sum_{s' \neq s} \left(No.\ Empl_{ls',t}/(No.\ Empl_{lt} - No.\ Empl_{lst})\right)^2.$$

We calculate these measures considering the total sample of firms in Fame, including firms in service industries. When variables are included at all levels simultaneously, variables are calculated removing the lower level from the higher one to have net agglomeration measures. Therefore, in the full model, agglomeration variables at the postcode area do not include agglomeration in the 3 × 3 km square around a firm and in turn, these do not include agglomeration at the 1 × 1 km square neighborhood.

4.2.3 | Firm-level characteristics

To control for possible confounding factors, we include a vector of firm-specific characteristics, such as *Firm Size*, we include two dummy variables for large and small companies, which assume value 1 if the firm has more than 250 employees in the year t (zero otherwise) and less than 50 employees in the year t (zero otherwise), respectively. The medium-sized firms are the baseline category (50-250 employees). *Firm Age*, we calculate the difference between the year of establishment and the current year, as a measure of cumulated experience in the market

Firm-level information is derived from Fame database. Table 1 summarizes our variables, and table 2 reports descriptive statistics. Estimates include sector fixed effects (when not subsumed by firm fixed effects) and a time trend.

5 | RESULTS

5.1 | Baseline results

We estimate several model specifications. In Mod. 1 we consider individual characteristics at the firm level in combination with agglomeration economies at the postcode area level. In the following models (Mod. 2–3) we progressively add agglomeration measures at finer spatial units, namely within-city 3 × 3 km square and firm 1 × 1 km neighborhood simultaneously. In each specification we include industry and year controls, allowing for the randomness in the intercept at each relevant level (i.e. firm and postcode area, as discussed in Section 4.1). Given that London represents a special case compared to other UK areas since only in the city of London there are eight different postcode areas, we exclude London in Mod. 4 as an additional robustness check.[10] Our baseline regressions are carried out using the mixed-effect (ME) model described in Section 4. As for Models 1–3 we also estimate a FE model, labeled with the postscript "a" to each model.

Table 3 reports the model estimates.

[10]Moreover, we perform two additional robustness checks, namely (1) in Mod. 5 (Table 3, column 9) we estimate the model including Northern Ireland; (2) in Mod. 6 (Table 3, column 10) we create the agglomeration variables at the highest level using the NUTS-3 administrative boundaries instead of the postcode area. Our main results persist.

TABLE 1 List of variables

Variable	Description	Level
Total factor productivity (TFP)	TFP of firm *i* at time *t*, throughout 2008–2016, using LP estimation technique (Levinsohn & Petrin, 2003)	Firm-sector
Small (dummy)	Dummy variable for small company, that assumes value 1 if the firm has less than 50 employees in the year *t*, 0 otherwise	Firm
Large (dummy)	Dummy variable for large company, that assumes value 1 if the firm has more than 250 employees in the year *t*, zero otherwise	Firm
Age (log)	Difference between the year of establishment and the current year of analysis (log)	Firm
Localization economies (log)	Number of employees working in the same industry *s* (2-digit NACE code)—outside the focal firm, and in the same location *l* (where *l* is the postcode area, within-city area, and neighborhood) at time *t*, where firm *i* is located (in log)	Postcode area/within the city/neighborhood
Urbanization economies: (i) Urbanization (log)	Number of employees in other industries in the area l (where *l* is the postcode area, within-city area, and neighborhood), at time *t*, where firm *i* is located (in log)	Postcode area/within the city/neighborhood
(ii) Industrial diversity	Inverse of Herfindahl index in the area *l* (where *l* is the postcode area, within-city area, and neighborhood), at time *t*	Postcode area/within the city/neighborhood

Note: Firm-level information is derived from Fame database, as well information about firm location relying on postcode information.
Source: Authors' elaboration from Fame database.

Findings underline that all firm-level individual characteristics have a positive and significant effect on productivity: firms that are larger and older (i.e., with a longer experience in the market) tend to perform better in terms of TFP. Coefficients and statistical significance are stable and consistent across ME and FE estimations. At the same time, agglomeration factors are significantly associated with firm productivity. This suggests that both individual and contextual factors matter.[11]

Results from Mod. 1 reveal that both *urbanization* and *localization* at the postcode area level have a positive and significant association with productivity. Among the sources of urbanization externalities, density of economy activity seems the key dimension, while a higher degree of industrial diversity does not have any significant correlation with productivity.

In Mod. 2 and 3 we include measures of *urbanization* and *localization* at a finer level of geographical disaggregation, using the within city areas around the firm. Findings reveals that the *urbanization* (density) is an important factor at a higher level of geographical aggregation—at the postcode area level, with a coefficient size greater and significant across specifications. On the other hand, *localization* plays a crucial role at a finer level of geographical disaggregation, in a closer neighborhood of the firm. Indeed, including the variables at 1 × 1 km level, we find that the role of *localization* externalities arises only in a closer neighborhood of the firm within the city,

[11]This conclusion is also supported by the value of the Likelihood Ratio test, which compares the multilevel model with an OLS regression, where the acceptance of the null hypothesis underlines that there is not significant difference between the two models, therefore the location (second-level) effect is negligible. In our case, the rejection of the null hypothesis underlines a hierarchical structure of the data, validating the multilevel approach.

TABLE 2 Descriptive statistics, panel data 2008–2016

Variable	Obs.	Mean	*SD* (overall)	*SD* (between)	*SD* (within)
DV: TFP-LP	30,565	5.536	1.252	1.239	0.555
Firm size: Large	30,565	0.097	0.296	0.252	0.118
Firm size: Small	30,565	0.319	0.466	0.460	0.168
Age (log)	30,565	3.119	0.824	0.904	0.173
City-wide (postcode area)					
Localization (postcode area)	30,565	6.887	1.956	1.987	0.360
Urbanization (postcode area)	30,565	11.937	1.007	0.999	0.143
Industrial Diversity (postcode area)	30,565	2.408	0.586	0.568	0.124
Within the city (3 × 3 km)					
Localization (3 × 3 km square)	30,565	3.379	2.902	2.843	0.650
Urbanization (3 × 3 km square)	30,565	5.715	4.693	4.574	1.272
Industrial diversity (3 × 3 km square)	30,565	1.137	0.980	0.953	0.287
Neighborhood (1 x 1 km)					
Localization (1 × 1 km square)	30,565	2.388	2.790	2.702	0.629
Urbanization (1 × 1 km square)	30,565	3.518	4.072	3.925	1.082
Industrial diversity (1 × 1 km square)	30,565	0.678	0.815	0.788	0.228

Source: Authors' elaboration from Fame database.

while at the more aggregate level the effect at the 3 × 3 km square disappears. Instead, *urbanization* at the city-wide (postcode area) level continues to have a positive effect on firms' productivity, while *urbanization* in a closer neighborhood does not have any significant effect, becoming negative at the neighborhood (1 × 1) level, possibly related to congestion effects. Thus, results support the idea that urbanization economies operate at a higher level of aggregation, while specialization economies require closer proximity between business parties, suggesting a role for the strength of industrial relationships among firms. It is worth noting that failing to control for within-city effects results in a spurious correlation that would wrongly support the coexistence of specialization and urbanization externalities at the postcode area level. Instead, when we appropriately control for the microgeography of agglomeration economies, effects of specialization economies are confined within a relatively small neighborhood around the firm. In sum, these findings suggest (i) a positive association between firm productivity and both localization and urbanization economies. However, results show that (ii) this relation is heterogeneous and depends on the geographical unit of analysis. Firms may benefit from being located in a more specialized neighborhood, within a diversified city. In other words, the local environment may be characterized by a combination of urbanization and specialization agglomeration economies, supporting the idea that (iii) these forces may "coexist" in the same area, but at different geographical scales.

It is worth mentioning that these findings are robust to a FE estimation, to the definition of the sample of locations included, and to an alternative definition of the highest level of geographical aggregation. First, if we compare Model 3 (our preferred specification) with Model 3a, we notice that in the FE model the coefficient associated with urbanization externalities at the postcode area is positive (and larger than the one estimated with ME model) but it is more imprecisely estimated and not statistically significant at conventional levels

TABLE 3 Agglomeration externalities and firm productivity

	Investigating Agglomeration economies at micro-geographical scales								
	Mod. 1	Mod. 1a	Mod. 2	Mod. 2a	Mod. 3	Mod. 3a	Mod. 4[a]	Mod. 5[b]	Mod. 6[c]
Estimation method	ME	FE	ME	FE	ME	FE	ME	ME	ME
DV: TFP-LP									
Firm size: Large	0.3050***	0.2091***	0.3044***	0.2084***	0.3053***	0.2085***	0.3116***	0.3056***	0.3042***
	(0.0352)	(0.0377)	(0.0354)	(0.0378)	(0.0353)	(0.0378)	(0.0356)	(0.0348)	(0.0380)
	([0.0000])	([0.0000])	([0.0000])	([0.0000])	([0.0000])	([0.0000])	([0.0000])	([0.0000])	([0.0000])
Firm size: Small	−0.3377***	−0.2255***	−0.3377***	−0.2256***	−0.3371***	−0.2242***	−0.3339***	−0.3370***	−0.3320***
	(0.0261)	(0.0388)	(0.0261)	(0.0388)	(0.0260)	(0.0389)	(0.0263)	(0.0253)	(0.0293)
	([0.0000])	([0.0000])	([0.0000])	([0.0000])	([0.0000])	([0.0000])	([0.0000])	([0.0000])	([0.0000])
Age (log)	0.2235***	0.3778***	0.2233***	0.3764***	0.2233***	0.3778***	0.2210***	0.2217***	0.2254***
	(0.0247)	(0.0621)	(0.0246)	(0.0621)	(0.0246)	(0.0620)	(0.0250)	(0.0243)	(0.0241)
	([0.0000])	([0.0000])	([0.0000])	([0.0000])	([0.0000])	([0.0000])	([0.0000])	([0.0000])	([0.0000])
City-wide (postcode area)									
Localization (postcode area)	0.0386*	0.0812**	0.0128	0.044	0.014	0.0441	0.012	0.013	0.0015
	(0.0205)	(0.0323)	(0.0201)	(0.0320)	(0.0200)	(0.0319)	(0.0208)	(0.0198)	(0.0164)
	([0.0600])	([0.0118])	([0.5256])	([0.1689])	([0.4845])	([0.1667])	([0.5648])	([0.5121])	([0.9286])
Urbanization (postcode area)	0.0567**	0.2178**	0.0622***	0.1139	0.0604***	0.1018	0.0648***	0.0565***	0.0827***
	(0.0245)	(0.0902)	(0.0199)	(0.0707)	(0.0199)	(0.0695)	(0.0214)	(0.0197)	(0.0198)
	([0.0208])	([0.0158])	([0.0018])	([0.1071])	([0.0023])	([0.1432])	([0.0024])	([0.0042])	([0.0000])
Industrial diversity (postcode area)	−0.0091	0.0211	−0.006	0.001	−0.0085	−0.0055	−0.0105	−0.0141	0.0155
	(0.0169)	(0.0300)	(0.0168)	(0.0292)	(0.0169)	(0.0291)	(0.0172)	(0.0173)	(0.0161)
	([0.5906])	([0.4824])	([0.7225])	([0.9726])	([0.6147])	([0.8508])	([0.5423])	([0.4161])	([0.3336])

(Continues)

TABLE 3 (Continued)

	Investigating Agglomeration economies at micro-geographical scales								
	Mod. 1	Mod. 1a	Mod. 2	Mod. 2a	Mod. 3	Mod. 3a	Mod. 4[a]	Mod. 5[b]	Mod. 6[c]
Estimation method	**ME**	**FE**	**ME**	**FE**	**ME**	**FE**	**ME**	**ME**	**ME**
Within the city (3 × 3 km)									
Localization (3 × 3 km)			0.0497	0.075	0.0013	−0.0051	0.012	−0.0006	0.0115
			(0.0326)	(0.0486)	(0.0198)	(0.0288)	(0.0195)	(0.0193)	(0.0185)
			([0.1276])	([0.1229])	([0.9494])	([0.8606])	([0.5377])	([0.9744])	([0.5347])
Urbanization (3 × 3 km)			−0.0161	0.0011	0.0136	0.0329	0.0085	0.0139	0.0143
			(0.0345)	(0.0510)	(0.0215)	(0.0310)	(0.0220)	(0.0211)	(0.0214)
			([0.6419])	([0.9827])	([0.5261])	([0.2882])	([0.6994])	([0.5106])	([0.5044])
Industrial diversity (3 × 3 km)			−0.0147	−0.0353	−0.0064	−0.0179	−0.0073	−0.007	−0.0065
			(0.0268)	(0.0354)	(0.0193)	(0.0274)	(0.0194)	(0.0189)	(0.0190)
			([0.5825])	([0.3186])	([0.7402])	([0.5130])	([0.7076])	([0.7116])	([0.7329])
Neighborhood (1 × 1 km)									
Localization (1 × 1 km)					0.0558*	0.1148**	0.0634*	0.0554*	0.0599*
					(0.0332)	(0.0530)	(0.0334)	(0.0323)	(0.0365)
					([0.0923])	([0.0302])	([0.0576])	([0.0866])	([0.1010])
Urbanization (1 × 1 km)					−0.0771*	−0.1174**	−0.0727*	−0.0731*	−0.0661
					(0.0437)	(0.0557)	(0.0447)	(0.0433)	(0.0442)
					([0.0778])	([0.0350])	([0.1034])	([0.0917])	([0.1344])
Industrial diversity (1 × 1 km)					0.027	0.0269	0.0204	0.0244	0.0165
					(0.0296)	(0.0361)	(0.0299)	(0.0292)	(0.0285)
					([0.3623])	([0.4570])	([0.4942])	([0.4036])	([0.5616])

TABLE 3 (Continued)

	Investigating Agglomeration economies at micro-geographical scales								
	Mod. 1	Mod. 1a	Mod. 2	Mod. 2a	Mod. 3	Mod. 3a	Mod. 4[a]	Mod. 5[b]	Mod. 6[c]
Estimation method	**ME**	**FE**	**ME**	**FE**	**ME**	**FE**	**ME**	**ME**	**ME**
Time (year)	−0.0016	−0.0180***	−0.0018	−0.0128**	−0.0018	−0.0122**	−0.0015	−0.0007	−0.0027
	(0.0030)	(0.0062)	(0.0031)	(0.0057)	(0.0030)	(0.0057)	(0.0031)	(0.0031)	(0.0028)
	([0.5984])	([0.0037])	([0.5490])	([0.0257])	([0.5541])	([0.0320])	([0.6248])	([0.8211])	([0.3249])
Constant	8.4546	40.6016***	8.9288	30.1757***	8.8576	28.9868**	8.3276	6.6677	10.7092*
	(6.0980)	(12.3693)	(6.1394)	(11.4572)	(6.0944)	(11.3691)	(6.2230)	(6.3168)	(5.5281)
	([0.1656])	([0.0010])	([0.1459])	([0.0085])	([0.1461])	([0.0108])	([0.1808])	([0.2912])	([0.0527])
Random-effects parameters									
Variance									
Postcode area (Intercept)	0.0048***		0.0047***		0.0048***		0.0051***	0.0057***	0.0025***
	(0.0050)		(0.0049)		(0.0050)		(0.0049)	(0.0048)	(0.0046)
	([0.0000])		([0.0000])		([0.0000])		([0.0000])	([0.0000])	([0.0013])
Firm (Intercept)	0.9979		0.9964		0.9973		0.9918	0.9911	0.9966
	(0.0574)		(0.0575)		(0.0576)		(0.0583)	(0.0564)	(0.0564)
	([0.9708])		([0.9508])		([0.9631])		([0.8892])	([0.8753])	([0.9522])
Total	0.3627***		0.3628***		0.3627***		0.3602***	0.3597***	0.3583***
	(0.0215)		(0.0215)		(0.0215)		(0.0216)	(0.0212)	(0.0234)
	([0.0000])		([0.0000])		([0.0000])		([0.0000])	([0.0000])	([0.0000])
Industry fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Robust std. errors	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Estimation method	Mixed	FE	Mixed	FE	Mixed	FE	Mixed	Mixed	Mixed

(Continues)

TABLE 3 (Continued)

	Investigating Agglomeration economies at micro-geographical scales								
	Mod. 1	Mod. 1a	Mod. 2	Mod. 2a	Mod. 3	Mod. 3a	Mod. 4[a]	Mod. 5[b]	Mod. 6[c]
Estimation method	**ME**	**FE**	**ME**	**FE**	**ME**	**FE**	**ME**	**ME**	**ME**
No. obs	30,565	30,565	30,565	30,565	30,565	30,565	30,079	31,294	29,993
No. postcode area	118		118		118		113	119	166
No. firms	4927	4927	4927	4927	4927		4836	5061	4848
Log- pseudolikelihood	−34,585.206		−34,585.477		−34,583.073		−33,927.644	−35,299.35	−33,786.92
R^2									
Within		0.02		0.02		0.02			
Between		0.05		0.05		0.05			
Overall		0.03		0.03		0.03			
Interclass correlation (ICC)									
Area	0.0034		0.0035		0.0035		0.0038	0.004	0.002
Firm/area	0.7340		0.7343		0.7343		0.7346	0.734	0.736

Note: Estimation method is either mixed-effects (ME) or fixed effects (FE)The dependent variable is the total factor productivity of 4297 single plants operating in manufacturing sectors, throughout 2008–2016. Agglomeration economies measures are standardized to facilitate comparisons across agglomeration types and spatial levels. Robust standard errors are reported in parentheses. p Values are reported in square bracket under the related coefficient and standard error. Asterisks denote confidence levels: $^{*}p < 0.10$, $^{**}p < 0.05$, and $^{***}p < 0.001$.

[a]Model 3 estimated excluding the area of London.

[b]Model 3 estimated including the manufacturing single-plant firms (134) located in Northern Ireland.

[c]Model 3 estimated using the NUTS-3 as the most aggregated geographical boundary, instead of the postcode area.

($p = 0.1432$). The coefficient associated with localization externality at the narrowly defined neighborhood (1 × 1 km) is positive and statistically significant. All in all, our findings are robust to the choice of the estimation method. As we will show in the next section, ME models lend themselves to further interesting explorations. Second, results are robust to the exclusion of firms based in London (Mod. 4) and to the inclusion of firms in Northern Ireland (Mod. 5). Finally, results are remarkably similar when we define the more aggregated geographical unit of analysis as NUTS-3, instead of postcode area (Mod. 6).

A few words of caution in interpreting our results are needed. On the one hand, our results show short-run correlations between agglomeration economies and firm productivity, conditional on time-invariant unobserved heterogeneity at the level of the firm, location, and sector. We also control for some time-varying firm characteristics. While we are confident that most sources of endogeneity have been accounted for, we cannot rule out the possibility that variation over time of agglomeration patterns and firm-productivity are jointly determined by some unobserved time invariant factor. Unfortunately, the practical difficulty to address this issue in our case is that agglomeration is measured at various flexibly defined geographical scales (such as the 1 × 1 km area around a firm) at which hardly information is available. On the other hand, our empirical design does not allow to address the issue of gross versus net agglomeration externalities. In particular, while we emphasize that the localized effects of specialization externalities fade with distance, we cannot rule out that the negative externalities require a larger area to appear. For example, transport costs and wages might depend much less on what happens in the small neighborhood and more on what happens in the larger area. Hence, we can only interpret our findings as the net effect of positive and negative externalities.

5.2 | Exploring sources of heterogeneity in firm benefits from agglomeration economies

So far, the two main results from the analysis are the positive and statistically significant effects of urbanization economies at the city-wide level and the localization economies at the 1 × 1 km neighborhood level. We can exploit the potentialities of the multilevel (mixed-effect) model to extend the analysis toward the investigation of an individual heterogeneous response to such agglomeration economies. In Table 4, we present the results of our main specification (Mod. 3, Table 3[12]), allowing for the randomness at the firm level in the slope of the urbanization economies at the postcode area and the localization economies at the (1×1 km) neighborhood level, as discussed in Section 4.1, Equations (3) and (4).

Results highlight a significant standard deviation suggesting that a component of heterogeneity does exist, while the mean effect of localization at 1 × 1 km neighborhood is now not significant, the standard deviation is significant, thus while some firms benefit significantly from agglomeration, others benefit much less, or may even be negatively affected. Indeed, this is consistent with some results that have been discussed in Section 2, highlighting that firms can benefit differently from agglomeration economies due to several possible factors, including those related to firm characteristics, as well as specificities of sectors and locations. A step forward would be the investigation of those factors affecting such heterogeneity, which can be done in several ways. The most commonly used methods to account for heterogeneous responses are splitting the analysis into subsamples by firm/industry/location factors or introducing interaction effects between the variable of interest (i.e., agglomeration economies) and the variables capturing firm, industry and location characteristics. However, both these approaches are not very efficient when the number of interactions increases. As proposed by Alcácer et al. (2018) and Castellani and Lavoratori (2020), heterogeneous responses can also be modeled by predicting firm-specific random parameters of

[12]We perform a Likelihood-ratio (LR) test discriminating between a model with random intercepts and random slopes and random intercepts only (i.e., Mod. 3, Table 3, vs. mod.3_random, Table 4). The test statistic $\chi^2(2)$ is equal to 770.89, which allows to soundly reject the restricted random intercept only model (p value = 0.0000).

TABLE 4 Agglomeration externalities and firm productivity – random slopes model

DV: TFP-LP	Mod. 3_random slopes Mean	*SD*
Firm size: Large	0.2915***	
	(0.0376)	
	([0.0000])	
Firm size: Small	−0.3189***	
	(0.0267)	
	([0.0000])	
Age (log)	0.2343***	
	(0.0256)	
	([0.0000])	
City-wide (postcode area)		
Localization (postcode area)	0.0165	
	(0.0209)	
	([0.4316])	
Urbanization (postcode area)	0.0604***	0.7306*
	(0.0222)	(0.1177)
	([0.0066])	([0.0514])
Industrial Diversity (postcode area)	−0.0047	
	(0.0174)	
	([0.7861])	
Within the city (3 × 3 km)		
Localization (3 × 3 km)	−0.0073	
	(0.0194)	
	([0.7059])	
Urbanization (3 × 3 km)	0.013	
	(0.0229)	
	([0.5725])	
Industrial Diversity (3 × 3 km)	0.0014	
	(0.0205)	
	([0.9455])	
Neighborhood (1 × 1 km)		
Localization (1 × 1 km)	0.048	0.4694***
	(0.0386)	(0.0693)
	([0.2133])	([0.0000])
Urbanization (1 × 1 km)	−0.0741*	

TABLE 4 (Continued)

DV: TFP-LP	Mod. 3_random slopes Mean	*SD*
	(0.0440)	
	([0.0923])	
Industrial Diversity (1 × 1 km)	0.03	
	(0.0323)	
	([0.3523])	
Time (year)	−0.0027	
	(0.0033)	
	([0.4160])	
Constant	10.5991	
	(6.6145)	
	([0.1091])	
Random-effects parameters		
Variance		
Postcode area (Intercept)	0.0029***	
	(0.0046)	
	([0.0002])	
Firm (Intercept)	0.6825***	
	(0.0604)	
	([0.0000])	
Total	0.3233***	
	(0.0228)	
	([0.0000])	
Industry fixed effects	Yes	
Robust std. errors	Yes	
Estimation method	Mixed	
No. obs	30,565	
No. postcode area	118	
No. firms	4927	
Log-pseudolikelihood	−34,197.626	

Note: The dependent variable is the total factor productivity of 4297 single plants operating in manufacturing sectors, throughout 2008–2016. Agglomeration economies measures are standardized to facilitate comparisons across agglomeration types and spatial levels. Robust standard errors are reported in parentheses. *p* Values are reported in square bracket under the related coefficient and standard error. Asterisks denote confidence levels: $^{*}p < 0.10$, $^{**}p < 0.05$, and $^{***}p < 0.001$.

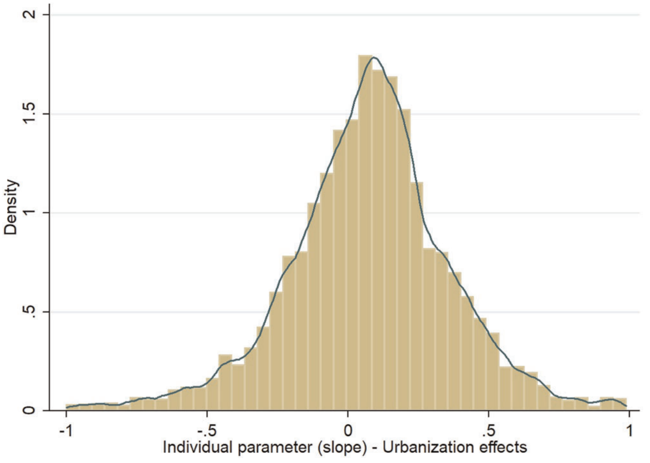

FIGURE 3 Kernel density distribution of the estimated firm-level parameter of Urbanization effects (postcode area). *Source*: Authors' elaboration [Color figure can be viewed at wileyonlinelibrary.com]

the variable of interest and modeling directly these parameters. We exploit the properties of mixed-effect models and go down this route. In particular, we first predict the value of the coefficients associated with our core independent variables for each firm-year observation in our sample,[13] then we plot their distributions, and investigate differences across firms in these distributions. Figures 3 and 4 show the kernel density distribution of the estimated firm-level parameters associated with urbanization at the postcode area and localization effects at the (1 × 1 km) neighborhood.

The two distributions show that individual coefficients of the elasticity of productivity to agglomerations are highly concentrated around the zero, with a mean slightly positive but a relatively large variance, underlying the presence of heterogeneous effects. A number of factors can explain such heterogeneity. Following some insights from the literature discussed in Section 2, we investigate whether the heterogeneous responses to agglomeration forces can be associated with sectors, such as high-tech versus low-tech industries following the classification provided by Eurostat, firm characteristics, such as age (*Below median age*, a dummy taking value 1 if the company's age is below the median age), productivity (*Above median TFP*, a dummy taking value 1 if the company's TFP is above the median TFP of the sample) and size (*Large firms*, a dummy taking value 1 if the company has more than 250 employees), or location characteristics, such as population density (*High population density* area dummy takes value equal to 1 if the firm is located in a postcode area with a population density[6] higher than the median level) and size of the postcode area (*Small area* dummy is equal to 1 if the size of the postcode area in square kilometer is smaller than the median).[14] In Figure 5, we plot the distributions conditional on these firm, sector, and location characteristics, and in Table 5 we statistically test the difference between the means performing a *t* test.[15]

It is worth noting that in our analysis the benefits from agglomeration differ indeed along several dimensions but not so much across sectors. As discussed in Section 2, externalities might be stronger in high-tech industries, where firms benefit more from knowledge spillovers (Caragliu et al., 2016). Figure 5 reveals that the distributions of the externality parameters for firms in high-tech and low-tech in our data are instead very similar. On average,

[13]We predict firm-specific coefficients using the post-estimation command `predict` of the `mixed post-estimation` package in Stata 14.

[14]This is done only for urbanization externalities at the postcode area, since localization have been identified over a fixed area of 1 km^2.

[15]We perform a *t* test using the `ttest` command in Stata 14.

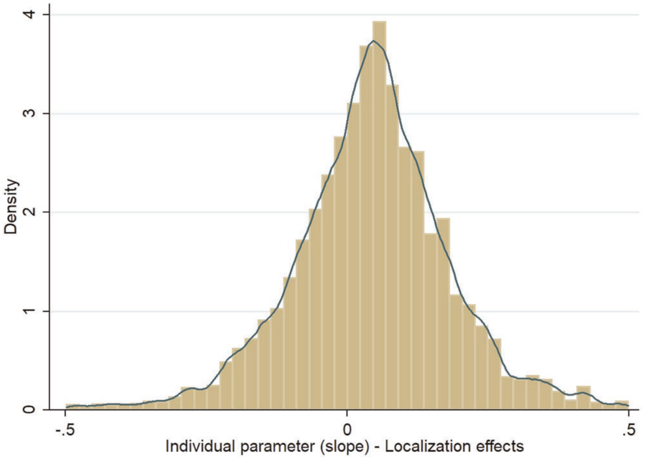

FIGURE 4 Kernel density distribution of the estimated firm-level parameter of Localization effects (1 × 1 km neighborhood). *Source*: Authors' elaboration [Color figure can be viewed at wileyonlinelibrary.com]

Table 5 indicates that firms in high-tech industry benefit more from urbanization and localization externalities, but this difference is small and not statistically significant.

Moving to firm characteristics, we can appreciate that younger firms tend to benefit more from urbanization economies, while older firms benefit more from localization economies. Though the difference in urbanization economies is small and not statistically significant. As noted by Duranton and Puga (2001, p. 1455), younger firms are in the learning stage of developing their products and their production process, so they need "to experiment to realize their full potential." Being located in a diversified environment can help the company in this search, boosting also innovation and the development of new ideas. Instead, older firms that have already developed their products and found their optimal production process, are more oriented toward cost saving and generation of economies of scale, thus being located in a strongly specialized neighborhood can generate benefits due to the presence of specialized suppliers and lower production costs (Duranton & Puga, 2001). Looking at the TFP level, more productive firms benefit more from urbanization, and less from localization. Firms that possess the best technologies, human capital, access to resources, distributors, and suppliers are those that contribute more to agglomerations, but the possible cost (and loss) due to knowledge outflows can be greater than the benefits of knowledge inflows from other companies, so being located in specialized areas can generate adverse selection mechanisms for this type of firms (Shaver & Flyer, 2000). Instead, more productive firms may be better able to extract returns from being located in an area with greater urbanization externalities (Combes et al., 2012), since these firms can benefit from cross-fertilization of ideas and innovation processes, and are able to bear the sunk costs to develop abilities to absorb and take advantage of such forms of agglomeration (Alcácer & Chung, 2007). These arguments are also consistent with the results on firm size: larger firms benefit more from urbanization, whereas there is no difference in terms of returns from localization.

Finally, in densely populated areas, returns from urbanization and localization are lower, and that is particularly true in the case of localization economies in the 1×1 km neighborhood, where congestion costs may be relatively higher. Additionally, we find that when the area is too small and population density high, returns from urbanization economies can hardly be generated, since these need bigger and diversified areas to mitigate the negative effects of agglomerations and some nonlinear spatial decay effects can appear (Cainelli et al., 2015).

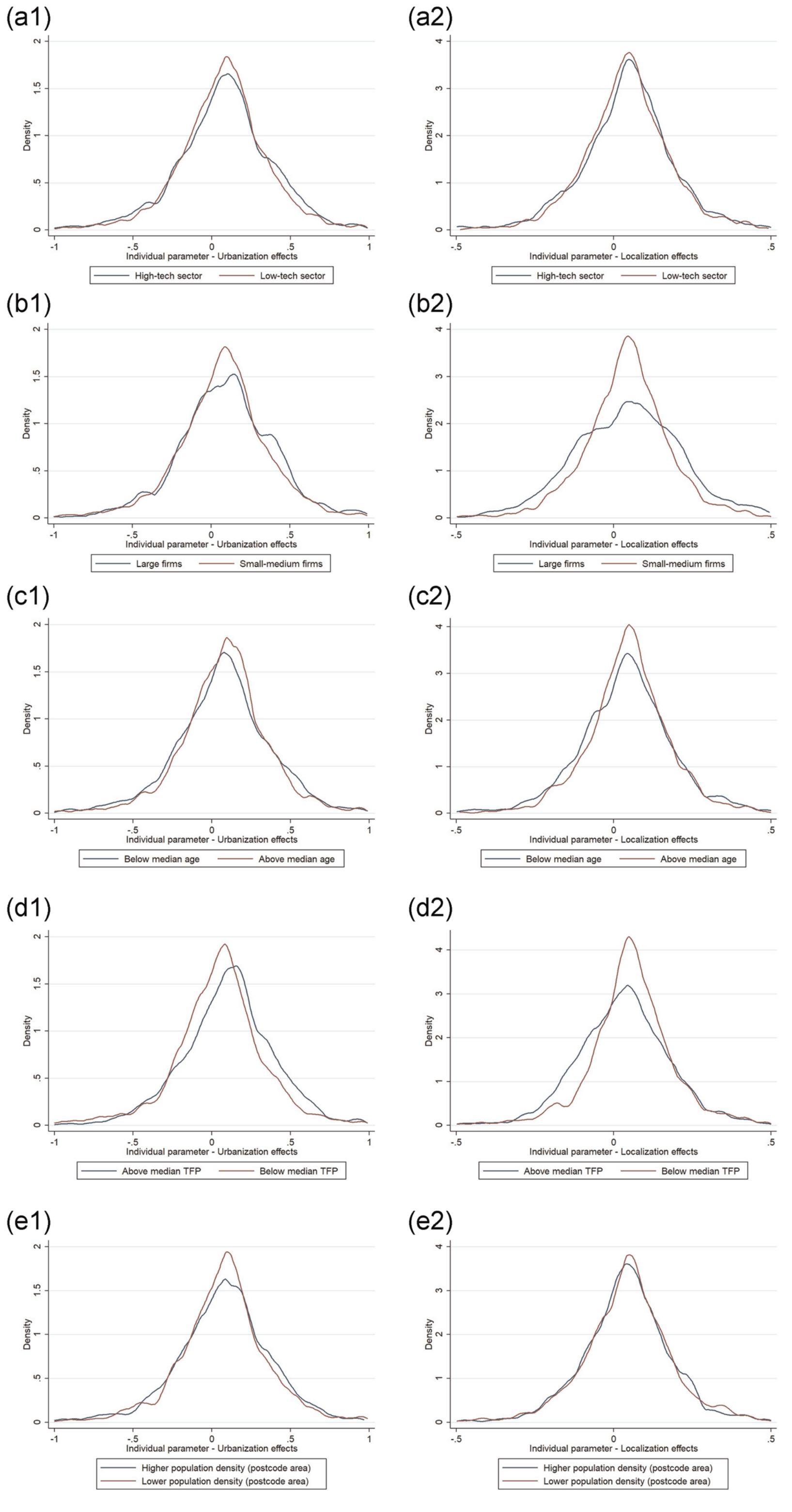

FIGURE 5 (See caption on next page)

6 | CONCLUSIONS

This study investigates whether firm productivity is associated with external agglomeration economies. A consistent body of the theoretical and empirical literature recognizes the extent of external urbanization and localization agglomeration economies, their role on location attractiveness, and the effect of agglomeration on industry, location, and firm growth, as well as on performance. However, the literature has not reached a consensus on the appropriate geographical unit of analysis to detect the effects of agglomeration externalities on productivity, and at which level of geographical unit *urbanization* and *localization* externalities operate.

Recent studies highlight that these two types of externalities may coexist in the same area rather than compete. Following this insight, we examine whether urbanization and localization externalities may operate at different spatial scales, but simultaneously. Using data on a sample of 4927 single-plant firms based in the United Kingdom and operating in manufacturing sectors over the 2008–2016 period, we estimate a multilevel mixed-effect analysis that allows to control for both individual and contextual characteristics affecting firm productivity, as well as to investigate the heterogeneity of individual firms' productivity to agglomeration economies.

Findings underline that urbanization externalities play a role at a higher level of geographical aggregation, which in our case corresponds to a city-wide area (and its immediate neighborhood) as delimited by the postcode area, whereas localization externalities operate at a finer level, within the city in a closer neighborhood to the firm (1 km^2), suggesting that proximity between economic parties is more conducive to increasing firm productivity when there is a closer industrial relationship. Also, our results suggest that failing to control for within-city effects may lead to wrongly support the coexistence of specialization and urbanization externalities at an aggregate level. Instead, when we appropriately control for the microgeography of agglomeration economies, effects are confined within the boundaries of the municipality.

Our analysis is in line with Andersson et al. (2019)'s results in the case of Sweden. The fact that these findings hold across two countries—which, despite similarities in GDP per capita, show remarkably different profiles in terms of territorial disparities—speaks to their generalizability. In fact, while Sweden is a country with very mild regional inequality in per capita GDP, where the government have been particularly active in boosting regional growth and wellbeing in the periphery as well as in the main metropolitan areas, the United Kingdom ranks 6th in the OECD in terms of regional inequality and growth is disproportionately driven by the largest metropolitan areas. Our results point out that—despite a different aggregate picture in the regional distribution of economic activity, the mechanisms discovered at the microgeographical level of analysis hold: specialization externalities occur in very narrow geographies, while the benefits of urbanization externalities can be achieved over larger geographical scales, although contained within a city-region.

Moreover, by exploiting the properties of mixed-effect models, we also provide novel evidence on the heterogeneity of agglomeration economies across firm and location characteristics. In particular, we show that a high population density reduces the potential for specialization externalities. Similarly, urbanization externalities require a city-region to be large enough to generate the sufficient benefits from the variety of economic activities. Furthermore, firms do benefit differently from agglomeration economies. While older and relatively less

FIGURE 5 Exploring the heterogeneity in firm-level parameters. (a) High tech versus low tech sectors. (b) Large versus small-medium firms. (c) Older versus younger firms. (d) More versus less productive firms. (e) High versus low population density. Number of observations 30,565. Below Median Age dummy (whether the company's age is below the median age), Above median TFP dummy (whether the company's TFP is above the median TFP of the sample), LEs dummy (whether the company has more than 250 employees, following the Eurostat classification) allowed to vary across years. High density area dummy (whether the firm is located in a postcode area with a population density higher than the median) computed using data on the 2011 Census. High-tech sector dummy, whether the sector is classified as high or medium-high tech following the classification provided by Eurostat (NACE 2-digit 20, 21, 26, 27, 28, 29, 30). *Source*: Authors' elaboration from Mod. 3, Table 4 [Color figure can be viewed at wileyonlinelibrary.com]

TABLE 5 Exploring heterogeneity of estimated firm-level parameters, t-test

	Urbanization—postcode area					Localization—1 × 1 km				
	Mean (0)	Mean (1)	Δ	*t*	*p* Value	Mean (0)	Mean (1)	Δ	*t*	*p* Value
High-tech sector	0.0669	0.0706	−0.0037	−0.6890	0.49	0.0459	0.0463	−0.0004	−0.1678	0.87
Below median age	0.0650	0.0713	−0.0063	−1.2195	0.22	0.0489	0.0433	0.0056	2.3001	0.02
Above median TFP	0.0368	0.0996	−0.0628	−12.2048	0.00	0.0582	0.0338	0.0244	9.9955	0.00
Large	0.0597	0.1468	−0.0870	−10.0052	0.00	0.0457	0.0494	−0.0037	−0.9032	0.37
High density area	0.0732	0.0634	0.0098	1.8973	0.06	0.0521	0.0402	0.0119	4.8484	0.00
Small area	0.0797	0.0565	0.0232	4.4960	0.00					

Note: *t* Test (mean-comparison tests) using the `ttest` command in Stata 14. Number of observations 30,565. “Below Median Age” dummy is equal to 1 if a company's age is below the median age, “Above median TFP” dummy is equal to 1 if a company's TFP is above the median TFP of the sample, “Large” dummy is equal to 1 if a company has more than 250 employees (following the Eurostat classification) allowed to vary across years. “High-tech sector” dummy is equal to 1 if the sector of the firm is classified as high or medium-high tech following the classification provided by Eurostat (NACE 2-digit 20, 21, 26, 27, 28, 29, 30). “High density area” dummy is equal to 1 if a firm is located in a postcode area with a population density higher than the median, computed using data on the 2011 Census. “Small area” dummy is equal to 1 if a firm is located in a postcode area with a size in square kilometer smaller than the median, this is done only for urbanization externalities at the postcode area, since localization have been identified over a fixed area of 1 km^2.

productive firms enjoy the cost-reducing benefits of proximity to firms in the same industry (specialization externalities) and in a narrow geography, younger, more productive, and larger firms benefit more from urbanization externalities over wider geographical areas.

Our research is obviously not free from limitations and our findings can stimulate further investigation. First, agglomeration effects may differ according to the type of firms that agglomerate in a certain location. For example, multinational firms and inward FDI may lead to stronger productivity effects (Bournakis et al., 2019; Driffield, 2006; Mariotti et al., 2015). Through the identification of multinational firms, one could be able to create measures of MNEs' participation in a local environment, to detect the role of ‘multinational' agglomeration externalities and FDI spillovers on firm performance, at different spatial scales simultaneously, in the spirit of a recent empirical study based in Vietnam (Kyburz & Nguyen, 2017). The interplay between the geographical scale of agglomeration externalities and MNEs can also be investigated from a different perspective. In particular, research could focus on the geographical boundaries of agglomeration economies as driving factors influencing the location decisions of foreign multinational companies (Lavoratori & Piscitello, 2021; Lavoratori et al., 2020). Second, our study suggests a novel way on how to exploit detailed firm micro-level data to draw an in-depth analysis aimed at investigating the role of firm, industry, and location heterogeneity on studies about agglomeration economies. Due to data limitations, we could investigate only a handful of such moderating conditions. However, results point to an important role of firm and location characteristics. Future research could further address this microfoundation aspect of agglomeration economies and carry out a more in-depth investigation of the sources and mechanisms of such agglomerations at different geographical levels (Andersson et al., 2019; Beaudry & Schiffauerova, 2009; Faggio et al., 2017; Puga, 2010).

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DATA AVAILABILITY STATEMENT

The data that support the findings of this study are available from Fame—Bureau van Dijk. Restrictions apply to the availability of these data, which were used under license for this study. Data are available from the authors with the permission of Fame—Bureau van Dijk.

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