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Mysteries of the trade? Skill-specific local agglomeration economies

Martin Andersson[a] and Johan P. Larsson[b]

ABSTRACT
Do workers benefit from proximity to other workers with similar skill sets? This question dates back at least to Alfred Marshall. We use occupation groups to proxy skill sets and show that the answer likely depends on geographical levels, as well on regional hierarchy. Using longitudinal Swedish data, we document robust evidence consistent with highly localized spillovers at the level of sub-city districts between individuals in similar occupations. We further demonstrate less distance-sensitive benefits of working in districts and regions, characterized by high overall density (of employees in other occupations). We find no evidence of benefits from overall density outside Sweden's three main metropolitan areas.

KEYWORDS
agglomeration economies; wages; spillovers; attenuation; clusters; economic proximity; relatedness

JEL J24, R10, R12
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INTRODUCTION

Alfred Marshall's narrative, wherein 'the mysteries of the trade become no mysteries' through knowledge 'in the air' may well be among the most exhausted quotes in the regional sciences (Marshall, 1920). Yet, it has often come to represent knowledge spillovers in general, rather than learning among workers with similar skills that Marshall had in mind when he spoke of the benefits 'people following the same skilled trade get from near neighborhood to one another'. Even though the skills involved may have changed, as well as what constitutes 'near neighborhood', Marshall identified a mechanism that remains underexplored in the empirical literature on agglomeration economies.

Following Marshall's idea that benefits of local density are stimulated by workers with similar skills, we investigate the relationship between wage gains and close proximity to workers with similar occupations. We provide new empirical evidence on these issues by analysing how agglomeration gains within metropolitan areas depend on a combination of proximity and skill similarities, as evidenced by occupational domains. More specifically, we ask whether working in sub-city districts with a high density of workers with similar occupations boosts wages.

Skills do constitute a central perspective in the recent literature through growing evidence of a 'skill bias' in agglomeration economies. A large body of evidence suggests that the nature of agglomeration gains has shifted towards a greater emphasis on contexts in which knowledge, technology and interactions between workers as well as firms are important (Glaeser & Kohlhase, 2003). This shift has imprinted the specialization patterns of cities in several ways, with notable effects on the types of activities and skills that benefit from being located in agglomerations.

One stream of the literature shows that 'economies of density' primarily pertain to knowledge-intensive workers and tasks intensive in interaction (Andersson et al., 2014; Bacolod et al., 2009; Glaeser & Resseger, 2010). Another

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stream studies patterns of specialization across cities and finds that they are increasingly specialized by function, where headquarter functions and other skill-intensive services cluster in large cities and production in smaller cities (Duranton & Puga, 2005). Studies of the long-run development of the occupational structure of cities in the United States further show that the employment share of occupations associated with interactivity has increased at a faster pace in metropolitan areas compared with other places (Michaels et al., 2019). Baum-Snow et al. (2018) find that a significant share of the increase in urban wage inequality between skilled and unskilled workers is explained by a skill bias in agglomeration economies. Their analysis further points to the growing importance of knowledge spillovers as a source of agglomeration economies as this mechanism appears to explain a large part of the overall relationship between city size and wages. Taken together, these developments constitute part of a broader transformation wherein skill-biased technological change (Autor et al., 2003) and the development of global value chains imply that the comparative advantages of many advanced countries have shifted towards activities and functions performed by skilled workers who benefit from agglomeration economies (Baldwin, 2016; Cheshire et al., 2014).

Despite evident changes in the nature of agglomeration economies, significant gaps remain in our knowledge of the mechanisms of their operation. While knowledge spillovers appear to be a more important source of agglomeration economies in recent times, there is limited evidence on how such spillovers are distributed within cities, and if they depend on similarities in occupation, industry or technology. Regarding spatial scales and attenuation, for instance, Parr (2002) argues that external economies cannot be fully understood or expressed outside of their spatial setting, but it is not fully explored what that exact setting is. We add to the analyses of these questions by using geocoded worker-level panel data to assess, first, the spatial distribution of spillover effects within cities and, second, whether spillover effects are contingent on skill similarities, as evidenced by workers' occupational belonging.

Background and motivation

The main questions that we set out to assess are whether we observe evidence of agglomeration gains between workers with similar skills, as evidenced by similar occupation, and to what extent such agglomeration gains require close proximity. These questions relate to two main strands of the literature: (1) on the geography and attenuation of agglomeration economies; and (2) on the role of economic proximity (or relatedness) in facilitating spillover effects between firms as well as workers. A main idea in the first set of studies is that geographical proximity between firms and people facilitates productivity gains through agglomeration economies. The studies depart from this insight and analyse how the strength of agglomeration economies attenuates with distance. Empirical studies in this vein typically find that agglomeration effects operate at different spatial scales. The evidence is consistent with agglomeration effects operating at small spatial scales inside cities, confined to sub-city districts or neighbourhoods (Andersson et al., 2019; Arzaghi & Henderson, 2008; Larsson, 2014; Lavoratori & Castellani, 2021; Rosenthal & Strange, 2003, 2008). This type of localized agglomeration effect is typically assumed to reflect knowledge spillovers, since they are more likely than other mechanisms to require close proximity and thus prone to operate at finer spatial scales (Arzaghi & Henderson, 2008; Rosenthal & Strange, 2020).[1]

The second strand of the literature to which our paper relates analyses the role of economic proximity (or relatedness) and highlights that geographical proximity is not enough to generate productive spillovers. Instead, it is a combination of geographical proximity and some form of economic proximity with regard to similarity in knowledge bases, skills, technology or industry that drives productive spillovers (Boschma, 2005; Frenken et al., 2007; Hidalgo et al., 2018).[2] Conceptually, this line of argument is based on several different schools of thought. One is the role of absorptive capacity for the efficient transmission of knowledge (Cohen & Levinthal, 1990). Another is the so-called 'French school of proximity' that emphasizes various dimensions of proximity (Carrincazeaux et al., 2008; Gilly & Torre, 2000; Torre & Rallet, 2005). There is also a literature based on the idea that the balance between cognitive proximity and distance matters for spillovers and learning (Boschma, 2005; Nooteboom, 2000). Just as Williamson (1985, pp. 18–19) claimed that 'transaction costs are the economic equivalent of friction in physical systems', economic proximity (or relatedness) between knowledge or technology domains is claimed to reduce frictions in the transmission of knowledge, information and ideas. A sizeable body of evidence supports this claim. For instance, analyses of human capital spillovers as well as spillover effects associated with large plant openings point to stronger spillover effects in the presence of geographical *and* economic proximity between firms as well as between workers (Greenstone et al., 2010; Moretti, 2004). There is also evidence that a variety of related industries in a region boosts employment growth (Frenken et al., 2007; Wixe & Andersson, 2017), and that relatedness between technologies and skills boosts the development of new specializations in cities and regions (Boschma et al., 2015; Neffke et al., 2011; Rigby, 2015; Xiao et al., 2018). Empirical analyses have employed various strategies to assess economic proximity and relatedness, including input–output linkages between industries, degree of sharing of workers and skills, sharing of technology as well as similarities as evidenced by industry classification systems (e.g., Moretti, 2004; Neffke & Henning, 2013).

Combining perspectives from these two literatures leads to two conjectures about likely mechanisms that explain how agglomeration gains depend on distance as well as skill similarities. First, knowledge spillovers are likely to operate at small spatial scales, such as city neighbourhoods or city districts. Second, effective knowledge spillovers require not only close geographical proximity, but also economic proximity (or relatedness). This implies that sub-city 'clusters' of related activities, that is, places where economic agents experience *both* economic and physical proximity, should be hotbeds for productive knowledge spillovers. Since knowledge spillovers constitute a main micro-foundation of agglomeration economies (Duranton & Puga, 2004), we expect firms and workers who operate near related activities to be more productive on average. This is the proposition that we aim to test in this paper. We contribute with an empirical analysis using geocoded panel data that allow us to account for small spatial scales, and to account for the role of economic proximity and skill similarity. Thereby, we provide novel empirical evidence of relevance to both types of the literatures.

Contribution

The literature on the geography and attenuation of agglomeration effects and the literature on the role of economic proximity have so far developed in parallel (Andersson et al., 2019). The attenuation literature has focused on empirically assessing the distance decay of agglomeration effects as well as of human capital spillovers (e.g., Andersson et al., 2016; Arzaghi & Henderson, 2008; Rosenthal & Strange, 2008) with little attention paid to the influence of various forms of economic proximity. The literature on economic proximity and relatedness, on the other hand, has not paid sufficient attention to the scale at which agglomeration effects operate and typically use whole regions or cities as their spatial level of analysis (e.g., Frenken et al., 2007; Neffke et al., 2011; Rigby, 2015). Agglomeration effects operating at small spatial scales may then be under identified. Some recent papers use detailed geographical data and assess the relative roles of industry specialization and industry diversity on the productivity of firms and establishments at different spatial scales (e.g., Andersson et al., 2019; Lavoratori & Castellani, 2021). One finding from this burgeoning literature is that spillovers channelled through industry specialization appear to be more bounded in space than effects of industry diversity. This paper adds to these recent analyses in five main ways:

- We analyse the issue at the level of the individual. The bulk of existing empirical analyses has either used industry-region or firm-level data and focused on outcomes such as employment growth, productivity, average wages and birth of new establishments. For example, Andersson et al. (2019) employ firm-level data and study the effect of sub-city industry clusters and find that significant effects on total factor productivity of firms in close proximity to other firms in the same industry. In this paper, we employ matched employer–employee data to assess if employees in sub-city clusters of workers with related jobs are more productive, as evidenced by wage gains. Even though individual workers are key 'agents' in the context of spillovers, few analyses in this vein have employed individual employee-level data to assess either the geography of agglomeration effects or the influence of economic proximity or relatedness.[3]
- We make use of finely geocoded data and an exogenous partition of cities based on a grid of 1 × 1 km squares. The detailed geocoding allows us to 'unpack' cities and identify spillover effects that operate at the level of sub-city districts, and we also assess the extent of attenuation by incorporating spatially lagged effects through the grid.
- We assess the role of economic proximity by analysing whether estimates of spillover effects from close geographical proximity to other workers are conditional on skill similarities, as evidenced by occupational domains. Rather than focusing on industry belonging, we follow Marshall's (1920) original narrative of skilled trades and focus on the tasks that workers perform. Similar occupational domains imply that workers, although employed in different industries and organizations, perform similar tasks and functions. Occupational similarity thus bodes for cognitive proximity between workers that can facilitate the potential for productive spillovers (cf. Nooteboom, 2000). For individual workers, the occupation may be thought of as a representation of the functional orientation of tasks and constitutes a relevant context for acquiring experiences and skills. The literature on 'occupational communities' in organizations links problems in communication and misunderstandings between workers with different functions, such as engineers, technicians and assemblers, within one and the same firm precisely to the fact that they have different work contexts and situated experiences (e.g., Bechky, 2003). The source of such communication problems is thus claimed to be related to the specialization inherent in performing their task, which implies that they develop different types of experiences and perspectives. This illustrates the role of the functional orientation of work experience for the potential for productive spillovers. For example, it is easy to imagine that managers and marketing professionals can learn, copy behaviours from each other, or exchange information and experiences on issues of workforce management and marketing strategies, although they work in different types of firms and/or different types of industries. Likewise, a software engineer in a small software development service firm may productively interact and exchange experiences and information with software engineers who develop software in a car manufacturing company (see Desrochers & Leppälä, 2011, for more examples and discussions along these lines). There is also empirical evidence suggesting that relevant human capital appears to be occupation specific, rather than industry or firm specific (Gathmann & Schönberg, 2010; Kambourov & Manovskii, 2009). Such results indicate that human capital in the form of a worker's experiences and skills in an occupation is transferable across firms and industries as long as they keep performing similar tasks. If occupational experiences and skills are transferable across firms and industries, then it should also be

possible for knowledge, ideas and information to spill over between workers within similar occupational domains.

- We exploit the richness of the data to assess the effects for different types of workers. A large empirical literature documents that the influence of agglomeration characteristics is heterogenous and industry dependent (Faggio et al., 2017; Groot et al., 2016) as well as the type of job and worker (Andersson et al., 2014; Autor, 2019; Bacolod et al., 2009). A consistent finding in the previous literature analysing skill biases in regional data is that agglomeration gains are driven by high-tech and more knowledge-intensive industries. The latter literature shows strong agglomeration effects for highly educated workers and workers with job tasks associated with social interactions, problem-solving and creativity. In this paper, we analyse these questions in an intra-city analysis of individual workers by estimating our models for workers in different industries and with different types of jobs.
- Skill biases in agglomeration economies and knowledge spillovers are typically associated with primarily larger urban areas, cities or metropolitan areas. The baseline in our empirical analysis is therefore Sweden's three largest cities, that is, Stockholm, Gothenburg and Malmo. However, some analyses find that there are differences between high- and low-density regions in terms of the role of agglomeration (Groot et al., 2016; Marrocu et al., 2013). Moreover, recent contributions have argued that the empirical research is too focused on large urban areas and that policy prescriptions typically focus on ways of making 'large cities bigger' (Rodriguez-Pose & Storper, 2020). For this reason, we also estimate our models for areas outside the main urban regions in Sweden, which allow us to assess if the spatial distribution of spillovers and the role of skill similarity differs between urban areas and less dense regions.

In summary, the previous literature supports that knowledge spillovers are bounded by both proximity and domain specificity, although the extents remain empirical questions. Our main contribution to the literature is a detailed worker-level analysis of the role of occupation similarity in facilitating spillover effects, together with an analysis of the attenuation of such spillovers with distance. Does occupation similarity facilitate spillovers and do such spillover effects accrue to the neighbourhood level within cities or can we observe them over larger areas?

Empirical analysis and summary of the main findings

Our empirical analysis employs geocoded matched employer–employee data on workers in Swedish cities from 2002 to 2013. We estimate Mincerian wage equations to assess whether working in a city district with many other workers in similar occupations boosts wages for various sets of skilled individuals. We include individual fixed effects (FE) and a rich set of control variables. All models include two types of variables reflecting the external environment, measured at three different spatial scales. For each worker, we measure the local density of same-occupation workers and also include another variable measuring density of all other workers. Both variables are measured in terms of the number of workers outside their own workplace, the size and skill composition of which we also control for. Both types of variables are computed at three spatial levels: (1) the within-city district (1 × 1 km square); (2) first-order neighbours, that is, eight neighbour squares; and (3) the labour market region. Hence, we assess whether evidence of effects operates at different scales, and thereby if it attenuates across different levels. To test the argument that the role of agglomeration effects matters more for knowledge- and interaction-intensive occupations (Andersson et al., 2014; Bacolod et al., 2009), we run separate models for different types of occupations and industries.

Our results are consistent with agglomeration benefits associated with working in a district with a high density of workers with the same occupation. We further uncover some evidence of working in environments of high overall density. This estimated effect is not as strong at the local level, but less distance sensitive and it generally spans entire labour markets. In non-metropolitan areas, we find weak effects at best of this overall density effect. The results are in line with the existence of a skill bias, since the evidence primarily supports district-level agglomeration gains for highly skilled individuals who work in city districts dense in similar skills, although supported by dense surroundings.

DATA

Matched employer–employee panel data

We employ geocoded matched employee–employer panel for Sweden spanning 12 years (2002–13). The data are register data (maintained by Statistics Sweden) covering the population of workers in Sweden in both manufacturing and services industries. Employees are assigned to their work establishment in November each year. Plants are in turn assigned to a firm. While the location of a firm can be difficult to determine because a firm may have several establishments (or plants) located in different regions or districts within cities, each establishment has a unique location and industry affiliation.

Though the data span all sectors of the economy, we exclude all public sector employees and workers in the agriculture and mining industries.[4] This isolates workers whose wage formation is determined by market outcomes and workers in sectors whose locations are not directly linked to natural resources. We also focus on workers in the age interval 20–64 and exclude the self-employed. Moreover, we only include workers for whom information on occupation is available.

To measure skill similarity, we employ three-digit occupational codes based on the International Standard Classification of Occupations (ISCO-88), although we also present the results using two- and four-digit groupings to test the sensitivity of our results to the level of classification employed. This implies that we make use of 112 occupational bins at the three-digit level to identify workers who have occupations that have similar skills, that is, occupational bins are used as a proxy for skills. One motivation for using ISCO-88 occupational groupings to discuss skills is that the definition of ISCO-88 groups is based on two dimensions of the skill concept: (1) skill level, which is based on the range and complexity of the tasks involved; and (2) skill specialization, which is based on the type of knowledge applied, tools and equipment used, materials worked on, or with, and the nature of the goods and services produced. The International Labour Organization (ILO) claims that:

> the focus in ISCO-88 is on the skills required to carry out the tasks and duties of an occupation and not on whether a worker in a particular occupation is more or less skilled than another worker in the same or other occupations.[5]

Against this backdrop, we argue that having the same three-digit occupational bin in ISCO-88 should capture relevant aspects of skill similarity between workers.

The data inform about several characteristics of each employee and their employer. For employees we have information such as education length, sex, age and wage income. At the level of establishments, we have information on location, total number of employees as well as sector affiliation. For firms we have balance sheet information, including book value of physical capital assets.

Geocoding: 1 × 1 km squares

Each establishment is associated with a geocoded cell in a country-wide grid of 1 × 1 km squares. We refer to these squares as city-districts. The geocoding is exogenous because the size as well as the position of the squares are independent of underlying economic activity. Many standard geographical delineations are directly dependent on economic activity, resulting in a built-in endogeneity risk, which we avoid. The squares further reflect a granular spatial scale consistent with the growing literature on attenuation, which shows that there are relevant externality effects that operate at small spatial scales (Andersson et al., 2019; Arzaghi & Henderson, 2008; Rosenthal & Strange, 2008).

The underlying 'true' scale of agglomeration effects could of course cover several squares.[6] By construction of the grid, each district, *d*, has eight first-order neighbours (Figure 1). In the analysis, variation at the sub-regional scale is captured at the levels of districts and of first-order neighbours. By including districts as well as first-order neighbours, we test for the attenuation of effects at a fine spatial scale. The regressions also include regional-level measures, which in turn are discounted for any employment in each worker's district, *d*, and neighbouring districts, *n*(*d*).

We run our baseline models for all workers in Sweden's main metropolitan areas, that is, Stockholm, Gothenburg and Malmo, and focus the analysis on districts with at least 100 employees outside their own work establishment. We

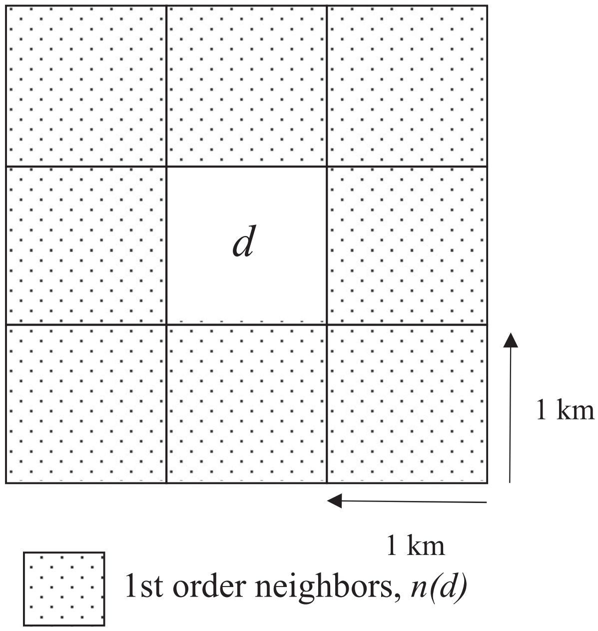

Figure 1. Squares and neighbours.

impose this cut-off in part for integrity reasons[7] and in part to ensure that minor events do not impact our results. We note that all results presented are insensitive to estimating the results without the cut-off. With these restrictions, our main dataset contains about 1.8 million metropolitan employees observed over a total of 10. 2 million individual years.

MODEL AND ESTIMATION

Baseline model

Our baseline model is a basic type of Mincerian wage equation. We use the model in (1) to estimate the influence that agglomeration variables at different spatial scales have on the wages of individual workers:

$$\begin{aligned} \ln w_{i,o,d,t} = & \gamma_1 \ln OC\_same^{district}_{o,d,t} + \gamma_2 \ln OC\_same^{neighbors}_{o,n(d),t} \\ & + \gamma_3 \ln OC\_same^{region}_{o,r,t} + \delta_1 \ln OC\_other^{district}_{o,d,t} \\ & + \delta_2 \ln OC\_other^{neighbors}_{o,n(d),t} + \delta_3 \ln OC\_other^{region}_{o,r,t} \\ & + \sigma_1 HC^{district}_{d,t} + \sigma_2 HC^{neighbors}_{n(d),t} + \boldsymbol{X}'\boldsymbol{\beta} + \theta_{o,i,t} \\ & + \rho_t + \lambda_i + \varepsilon_{i,o,d,t} \end{aligned} \tag{1}$$

where $w_{i,o,d,t}$ is the wage of worker *i* with occupation *o* working in district *d* in year *t*; and $\boldsymbol{X}$ is a vector of worker- and employer-level control variables. For individual workers it includes age, age squared and a dummy equal to 1 if the worker has a long university education (three or more years). At the level of the work establishment, we include the log of the number of employees of the establishment as well as a dummy for the main two-digit industry (NACE) in which the establishment is classified. We also include the fraction of workers with a university degree and the fraction of employees at the workplace who have the same three-digit occupation as worker i. These variables are intended to control for the overall level of human capital in at the workplace and also the extent of occupation specialization, which reflects productive opportunities at the workplace. At the firm level, we include the log of the book value of physical capital assets. We also include industry-year effects to account for industry-specifics shocks over time as well as a dummy which is 1 if the worker moved districts of employment between t and $t-1$.

In addition, the model includes occupation-specific effects ($\theta_{o,i,t}$) based on the worker's three-digit occupation (ISCO-88) in year t, year-specific effects common to all workers (ρ_t) as well as time-invariant worker heterogeneity (λ_i). The worker-level FE wipe out any time-invariant heterogeneity at the level of workers, such as innate abilities. For workers who do not move between workplaces or districts, they also wipe out time-invariant characteristics of districts and workplaces. The FE imply that a change in district employment can come about in two ways: (1) the worker moves their place of work from one district to another, or (2) there is a change in employment in the district where a worker is employed. In the regressions we include a dummy for individuals who move between districts between two years.

Our variables of main interest capture effects of proximity to workers outside their own work establishment. A main goal is to assess if the benefits of close geographical proximity to other workers are conditional on skill similarities, as evidenced by occupational domains. To this end, we develop two different agglomeration measures defined at three contiguous spatial scales. The first variable is $OC\_same^{district}_{o,d,t}$, which measures the number of employees working in the same district and in the same three-digit occupation as worker i. Formally:

$$OC\_same^{district}_{o,d,t} = EMP_{o,d,t} - L\_firm_{i,o,d,t} \quad (2)$$

where $EMP_{o,d,t}$ is the number of employees in district d with occupation o in year t; and $L\_firm_{i,o,d,t}$ is the number of workers with occupation o in their own place of work. This is the local density of workers with the same three-digit occupation as a worker in a district (1 km^2 square) and is intended to reflect the potential for productive spillovers between workers in different organizations, but active within a similar occupational domain.[8] Note that this measure is different for two workers who work in the same district if they have different occupations, because the local density of workers with different occupations is typically different within one and the same district. The measure can also be different for two workers who work in the same district and have the same occupation, provided that they work in firms of different size. The reason for this is that the measure captures the density of workers *outside* the firm in which a worker is employed.

We also develop an equivalent measure but defined at the level of neighbour districts (Figure 1):

$$OC\_same^{neighbors}_{o,n(d),t} = EMP_{o,n(d),t} \quad (3)$$

where $EMP_{o,n(d),t}$ refers to the sum of the number of employees with occupation o in the eight neighbour squares of district d, $n(d)$. By including both measures as separate variables, we analyse the attenuation of agglomeration effects pertaining to occupational domains. For example, if close proximity is central, γ_1 would dominate γ_2. Finally, we also include a measure at the regional level:

$$OC\_same^{region}_{o,r,t} = EMP_{o,r,t} - EMP_{o,d,t} - EMP_{o,n(d),t} \quad (4)$$

The model also includes measures of the employment density of employees in occupations other than o at each spatial level. At the level of districts, the number of employees with other occupations outside their own establishment is given by the total number of other-occupation workers outside their own workplace:

$$OC\_other^{district}_{o,d,t} = EMP_{d,t} - L\_firm_{i,d,t} - (EMP_{o,d,t} + L\_firm_{i,o,d,t}) \quad (5)$$

where $EMP_{d,t}$ is the total number of employees in district d. The same variable at the level of first-order neighbours $n(d)$ is given by:

$$OC\_other^{neighbors}_{o,n(d),t} = EMP_{n(d),t} - EMP_{o,n(d),t} \quad (6)$$

If productive spillovers are contingent on occupational domains, we expect that the estimated influence of $OC\_same^{district}_{o,d,t}$ dominates that of $OC\_other^{district}_{o,d,t}$. If instead it is the overall density that is important, we expect the opposite pattern. The corresponding regional level measure is given by:

$$OC\_other^{region}_{o,r,t} = EMP_{r,t} - EMP_{d,t} - EMP_{n(d),t} - (EMP_{o,r,t} + EMP_{o,d,t} + EMP_{o,n(d),t}) \quad (7)$$

We further include the fraction of the total number of employees with a long university education (three or more years) at the district and neighbouring districts, respectively. Several empirical analyses of human capital spillovers at the regional level document that local density of educated workers influences worker wages as well as the productivity of plants (Rauch, 1993; Moretti 2004). Therefore, we include the human capital in districts, $HC^{district}_{d,t}$, and neighbour districts, $HC^{neighbors}_{n(d),t}$, as control variables. These are defined as follows:

$$HC^{district}_{d,t} = \frac{EMP^{edu}_{d,t}}{EMP_{d,t}} \quad (8a)$$

$$HC^{neighbors}_{n(d),t} = \frac{EMP^{edu}_{n(d),t}}{EMP_{n(d),t}} \quad (8b)$$

where $EMP^{edu}_{d,t}$ and $EMP^{edu}_{n(d),t}$ are the total number of employees with a long university education in district d and in the eight neighbours of the same district, $n(d)$, respectively.

All variables are summarized in the descriptive Table A1 in the supplemental data online.

Estimates for subgroups of workers

After estimating our model for all workers, we exploit the richness of the data to explore the results for different subgroups of workers. A large empirical literature documents that the influence of agglomeration characteristics is heterogenous and industry dependent (Faggio et al., 2017; Groot et al., 2016) as well as the type of job and worker (Andersson et al., 2014; Autor, 2019; Bacolod et al., 2009).

We estimate our models for two different subgroupings of workers. First, we run models for workers by broad industry classifications. We separate between workers employed in manufacturing and low- and high-end services. Low-end services comprise basic services such as wholesale and retail trade, whereas high-end services include knowledge-intensive services, such as research and development (R&D), management consultancy and a wide range of business services.

Second, we run separate models for workers with different types of occupations, irrespective of their industry belonging. Like Andersson et al. (2014), we make use of a job-task classification scheme developed by Becker et al. (2013), which reports the fraction of non-routine job tasks associated by each ISCO-88 occupation. The classification is based on a German work survey, which reports answers to 81 questions regarding workplace tool use by occupation. Tools are codified according to whether or not the use of a tool indicates non-routine tasks. The classification in Becker et al. is similar to that of Autor et al. (2003) and Spitz-Oener (2006) in that occupations are linked to the involved share of routine versus non-routine tasks.[9] We use these data to estimate models for workers with occupations involving high (50% or more) and low (less than 50%) fractions of non-routine tasks, respectively. The literature on the skill-bias in agglomeration economies suggests that local agglomeration should matter more for knowledge-intensive industries and educated workers, as well as for workers with jobs with higher fractions of non-routine job tasks.

RESULTS

Metropolitan regions

Baseline results

The results from our baseline model in equation (1) are presented in Table 1. We begin by estimating the model for all workers with all variables included (column 1). We then estimate the model with district-level variables only (column 2), then with first-order neighbours (3), then with regional-level variables (4). Column (5) presents the complete model estimated with ordinary least squares (OLS) model in levels (without the individual-level FE, λ_i) for reference.

Looking first at the FE model with all variables included (column 1), it is clear that close proximity to the same occupation is significant and positive. There is also a positive effect of same-occupation workers at the levels of neighbours and of the wider region, although the point estimate at the level of neighbours is negligible. The fully specified model with FE in column (1) informs that the doubling of local density of same-occupation workers is associated with a wage increase of 0.5%. This is a lower point estimate compared with those pertaining to the regional-level variables, but for a variable with much higher underlying variability. A 'doubling of the density' at the level of city districts actually means something in practice, while 'doubling city density' is only a meaningful statement in a cross-section. As may be gauged from Table A1 in the supplemental data online, a 1 SD (standard deviation) increase in the number of same-occupation workers in the 'average' district will increase that occupation's local density by almost 200%, and a 1 within-SD represents more than a doubling. For first-degree neighbouring district variables, the ratios of SDs to averages are further magnified. These figures should be compared with the region-level variables where the SDs are a fraction of the averages. The results are consistent with economically significant localized spillover effects between workers with similar occupational domains. The variable tracking same-occupation workers in first-order neighbouring squares is positive and statistically different from zero, but of modest economic significance. Looking at columns 2–4 in Table A1, we also see that the main results are insensitive to specifications with each level included separately. Note in particular how the highly local effect of density of workers with the same occupation is *not* picked up at the level of neighbours when the district level is excluded (see column 3).

There is also a positive statistical association of being close to workers in *other* occupations, although the estimated point elasticity is smaller. The density of workers with other occupations also has lower variability, which means that it takes more significant relative changes in the local economy to accomplish a percentage change in density that leave footprints in workers' wages. The density of workers with other occupations can be interpreted as reflecting the overall density of the district. Our results show that overall density does matter, but that the density of workers with similar occupations has a stronger effect.

When we compare these results with the OLS model in column (5) we can conclude that there is a good deal of selection in the results without FE. In principle, all OLS coefficients are higher across the board. We take this as an indication that estimating the effects of agglomeration economies without accounting for sorting will lead to bloated coefficients (Combes et al., 2008; Ahlin et al., 2018). Nevertheless, the OLS results clearly show that wages are substantially higher for workers who work in clusters dense in own-occupation workers.

Turning to the control variables, we see that the estimated influence of the share of workers with a long university education (three or more years), net of controlling for the worker's own education, the share of employees in their own workplace with a university degree, and our full range of density variables, is negative. All FE coefficients are of modest economic importance, probably owing to the slow-moving nature of this ratio. Note that

Table 1. Influence of the density of workers with the same and other occupations on the wage income of workers *inside* metropolitan regions.

	(1)	(2)	(3)	(4)	(5)
District, (ln) density of workers with the same two-digit occupation	0.004**	0.005**			0.012**
	(0.000)	(0.000)			(0.000)
Neighbours, (ln) density of workers with the same two-digit occupation	0.000**		0.000**		0.001**
	(0.000)		(0.000)		(0.000)
Region, (ln) density of workers with same two-digit occupation	0.011**			0.013**	0.018**
	(0.001)			(0.001)	(0.001)
District, (ln) density of workers with other occupations	0.002**	0.001**			0.002**
	(0.000)	(0.000)			(0.000)
Neighbours, (ln) density of workers with other occupations	−0.001*		0.002**		−0.002**
	(0.000)		(0.000)		(0.000)
Region, (ln) number of workers with other occupations	0.022**			0.016**	0.020**
	(0.003)			(0.003)	(0.001)
District share university educated	−0.035**	−0.034**	−0.022**	−0.015**	−0.030**
	(0.003)	(0.003)	(0.003)	(0.003)	(0.002)
Share university educated (neighbours)	−0.018**	−0.021**	−0.016**	−0.003	−0.044**
	(0.004)	(0.004)	(0.004)	(0.004)	(0.002)
Age	0.058**	0.058**	0.058**	0.058**	0.052**
	(0.020)	(0.020)	(0.020)	(0.020)	(0.000)
Age squared	−0.001**	−0.001**	−0.001**	−0.001**	−0.001**
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
University education	0.276**	0.277**	0.277**	0.277**	0.046**
	(0.003)	(0.003)	(0.003)	(0.003)	(0.001)
Employer (ln) size	0.009**	0.009**	0.009**	0.009**	0.014**
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Firm share university educated	0.110**	0.110**	0.111**	0.112**	0.216**
	(0.002)	(0.002)	(0.002)	(0.002)	(0.001)
Firm share same occupation	0.060**	0.060**	0.062**	0.063**	0.068**
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
Capital (ln)	0.005**	0.005**	0.005**	0.005**	0.012**
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Mover	−0.016**	−0.016**	−0.016**	−0.016**	−0.044**
	(0.000)	(0.000)	(0.000)	(0.000)	(0.001)
Constant	6.214**	6.566**	6.560**	6.297**	6.759**
	(0.684)	(0.683)	(0.683)	(0.686)	(0.058)
Number of observations	10,174,640	10,174,640	10,174,640	10,174,640	10,174,640
R^2 (within)	0.136	0.136	0.136	0.136	0.369
Number of individuals	1,828,578	1,828,578	1,828,578	1,828,578	1,828,578
Year FE	Yes	Yes	Yes	Yes	Yes
Occupation FE	Yes	Yes	Yes	Yes	Yes
Industry FE	Yes	Yes	Yes	Yes	Yes
Year × Industry FE	Yes	Yes	Yes	Yes	Yes

Notes: Reported are the results from an estimation of the model in equation (1) with different specifications. Model 1 includes all variables. Model 2 only includes the district level, model 3 only the neighbourhood level and model 4 only the region level as regards our variables of main interest. As a reference, model 5 estimates the full model within levels/ordinary least squares (OLS). In models 1–4, all parameters are estimated with a panel estimator with worker-level fixed effects (FE). The underlying data are employees in districts (1 km^2 squares) with at least 100 employees within any of Sweden's main metropolitan regions, that is, Stockholm, Gothenburg or Malmo local labour market regions. Robust standard errors reported in parentheses.
$^{**}p < 0.01$, $^{*}p < 0.05$.

we do not include this control at the level of regions since we would simply lack ample variation across only three regions. The worker- and firm-level control variables behave as expected. Becoming older and attaining a long university education is associated with an increase in wage. An increase in the size of the establishment in which a worker is employed as well as an increase in the capital stock of the firm is also associated with wage increases. The share of workers in the firm having the same three-digit occupation as the worker in question is also positive, suggesting that more occupation-specialized organizations are more productive on average.

Taken together, the baseline results suggest that it is the local density of same-occupation workers at the district level (1 × 1 km squares) that appear to be associated with largest effects. Consistent with Marshall's original idea, they provide support for the idea that productive spillover effects that boost workers' productivity are facilitated by close proximity as well as skill similarities, as measured by occupational domains. The results also provide an economic rationale for the tendency of similar activities to cluster at the level of districts in cities, beyond similarities in bid–rent curves, because such clustering appears to bring productivity advantages.

Differences by industry and type of occupation

Table 2 turns to the industry- and occupation-disaggregated results. Columns (1) to (3) report the results for workers employed in manufacturing and low- and high-end services, respectively. Columns (4) and (5) show the respective results for occupations characterized by low (less than 50%) and high (50% or more) fractions of non-routine job tasks.

At the district level, the estimated influence of the density of same-occupation workers on wage remains positive across subgroups in all specifications. Doubling the number of workers with similar occupations is associated with an increase in the wage income of local workers of 0.3–0.4%, with the slightly higher point estimate coming from workers performing non-routine work tasks. Workers across the board thus appear to benefit from proximity to workers with similar occupations. A location in a sub-city cluster of workers with related occupations thus bring benefits to workers in different industries and different type of jobs.

Looking at the level of first-order neighbours, the estimated coefficients are generally small. This is consistent with highly localized agglomeration gains, confined to small spatial scales within cities. Working in regions dense in same-occupation workers is positively associated with wages in manufacturing and occupations rich in routine work tasks. The estimate is positive but of modest magnitude also in low-end services. However, for high-end services and workers with a high fraction of non-routine work tasks it is insignificant. For these subgroups, it seems to be mostly the district level that matters, as far as occupation clusters are concerned. This result may reflect that such activities are more dependent on knowledge spillovers, and if such spillovers operate at small spatial scales, then the wider region matters little. For routine work, manufacturing and overall services, on the other hand, knowledge spillovers may be less important. At the regional level, it is possible that many workers in similar occupations reflect other types of specialization effects, such as input suppliers and the local availability of subsidiary services, that is, effects that operate at wider spatial scales than knowledge spillovers.

The coefficient associated with density of other-occupation workers at the level of districts is positive for all subgroups except for manufacturing, but of negligible size in low-end services. We also observe estimates close to zero coming from neighbouring districts. At the level of the wider region, the number of other-occupation workers is statistically significant and positive for all groups but for manufacturing. It is also the case that the estimated elasticity is substantially higher for non-routine workers compared with routine workers. These results resonate with the idea that it is primarily non-routine occupations that may draw on local diversity and exploit cross-fertilizations between different types of economic activities (Duranton & Puga, 2001; Feldman & Audretsch, 1999). The fact that the influence of other-occupation workers appears to operate at all three spatial levels (with the exception of manufacturing) also suggests that the value of diversity in agglomeration economies may be less distance sensitive than occupation-specific spillovers. The control variables have a similar estimated influence as in Table 1.

Sensitivity of results to the level of occupational classification

An issue in any analysis that use classification schemes of occupations, industries or products concerns the appropriate level of the classification system. For example, this is a well-known problem in the literature on the relative role of industry specialization and diversity, in which a common issue has been that results at different levels of industry aggregation are varied (Beaudry & Schiffauerova, 2009; Groot et al., 2016). Previous literature has advised against high levels of industry aggregation, in particular when measuring specialization (e.g., Kemeny & Storper, 2015). In our empirical context, one concern is whether the occupational bins provide enough granularity at the occupation level to estimate distinct occupational spaces, and also if our main results are sensitive to the level of aggregation. Our choice of the three-digit level for the baseline results was made based on a combination of issues related to the granularity and distinctiveness of individual occupational bins.

However, it is impossible to determine a priori the 'correct' level of aggregation. To test if our main results are sensitive to the level of aggregation of occupational groupings, Table 3 presents results based on two- and four-digit levels of the ISCO-88 occupation grouping for the five subgroups in Table 2. This allows us to test whether our baseline results across subgroups hold if we employ more and less detailed groupings, respectively.

It is clear that the main results regarding the estimated influence of the density of same-occupation workers at the level of districts holds at both two- and four-digit levels. The only exception is that at the broad level of

Table 2. Influence of density of workers with the same and other occupations on the natural logarithm of wage income – panel fixed effects (FE) estimates for workers *inside* metropolitan regions.

	(1) Manufacturing	(2) Low-end services	(3) High-end services	(4) Routine skills	(5) Non-routine skills
District, (ln) density of workers with the	0.003**	0.003**	0.003**	0.003**	0.004**
same two-digit occupation	(0.000)	(0.000)	(0.001)	(0.000)	(0.000)
Neighbours, (ln) density of workers with	0.000	0.000**	0.000**	0.001**	0.000**
the same two-digit occupation	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Region, (ln) density of workers with same	0.015**	0.004*	0.002	0.013**	0.002
two-digit occupation	(0.002)	(0.002)	(0.003)	(0.002)	(0.002)
District, (ln) density of workers with other	−0.000	0.002**	0.005**	0.001*	0.002**
occupations	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
Neighbours, (ln) density of workers with	0.002*	0.001	0.002*	−0.001**	0.001**
other occupations	(0.001)	(0.000)	(0.001)	(0.000)	(0.000)
Region, (ln) number of workers with	−0.007	0.036**	0.028**	0.016**	0.031**
other occupations	(0.007)	(0.004)	(0.006)	(0.005)	(0.003)
District share university educated	−0.009	−0.031**	−0.011	−0.035**	−0.042**
	(0.009)	(0.005)	(0.008)	(0.005)	(0.004)
Share university educated (neighbours)	0.003	−0.018**	−0.015	−0.002	−0.024**
	(0.007)	(0.006)	(0.008)	(0.006)	(0.005)
Age	0.098	0.035	0.156**	0.050*	0.107**
	(0.081)	(0.020)	(0.037)	(0.019)	(0.010)
Age squared	−0.000**	−0.001**	−0.001**	−0.000**	−0.001**
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
University education	0.219**	0.206**	0.317**	0.143**	0.277**
	(0.010)	(0.004)	(0.007)	(0.004)	(0.005)
Employer (ln) size	0.010**	0.013**	0.008**	0.010**	0.007**
	(0.001)	(0.000)	(0.001)	(0.001)	(0.000)
Firm share university educated	0.049**	0.096**	0.072**	0.085**	0.081**
	(0.006)	(0.003)	(0.003)	(0.004)	(0.002)
Firm share same occupation	0.084**	0.057**	0.039**	0.066**	0.040**
	(0.003)	(0.001)	(0.002)	(0.001)	(0.001)
Capital (ln)	0.002**	0.004**	0.006**	0.004**	0.005**
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Mover	0.000	−0.018**	−0.004**	−0.028**	−0.002**
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
Constant	4.241	6.738**	3.031*	6.203**	4.654**
	(3.051)	(0.666)	(1.247)	(0.634)	(0.358)
Number of observations	2,086,287	5,934,156	2,268,019	4,801,037	5,487,425
R^2 (within)	0.114	0.111	0.123	0.081	0.138
Number of individuals	401,135	1,296,506	581,908	1,101,795	1,005,504
Year FE	Yes	Yes	Yes	Yes	Yes
Occupation FE	Yes	Yes	Yes	Yes	Yes
Industry FE	Yes	Yes	Yes	Yes	Yes
Year × Industry FE	Yes	Yes	Yes	Yes	Yes

Notes: Reported are the results from estimating equation (1) for five different groups of workers. Models (1) to (3) present the results for workers based on the industry affiliation of the establishment at which they are employed. Models (4) and (5) present the results for workers based on the fraction non-routine tasks associated with their occupation. *Routine* is composed of workers with occupations involving job tasks of which fewer than 50% are classified as non-routine. *Non-routine* are workers with occupations involving job tasks of which 50% or more are classified as non-routine. The underlying data are employees in districts (1 km^2 squares) with at least 100 employees within any of Sweden's main metropolitan regions, that is, Stockholm, Gothenburg or Malmo. Robust standard errors reported in parentheses.
$^{**}p < 0.01$, $^{*}p < 0.05$.

Table 3. Sensitivity analysis replicating the baseline model (Table 2) using three- and four-digit occupation classifications.

	(1) Manufacturing	(2) Low-end services	(3) High-end services	(4) Routine skills	(5) Non-routine skills
Two-digit results					
District, (ln) density of workers with the same two-digit occupation	0.001	0.003**	0.004**	0.002**	0.004**
	(0.000)	(0.000)	(0.001)	(0.000)	(0.000)
Neighbours, (ln) density of workers with the same two-digit occupation	−0.000	−0.000	0.000*	0.000	0.000*
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Region, (ln) density of workers with same two-digit occupation	0.037**	0.012**	0.004	0.017**	0.023**
	(0.003)	(0.003)	(0.005)	(0.003)	(0.003)
District, (ln) density of workers with other occupations	0.002	0.002**	0.004**	0.002**	0.003**
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
Neighbours, (ln) density of workers with other occupations	0.002**	0.001	0.002*	−0.002**	0.001*
	(0.001)	(0.000)	(0.001)	(0.000)	(0.000)
Region, (ln) number of workers with other occupations	−0.029**	0.028**	0.026**	0.012*	0.008
	(0.008)	(0.004)	(0.007)	(0.005)	(0.004)
Number of observations	2,086,315	5,934,153	2,267,998	4,801,089	5,487,377
R^2 (within)	0.113	0.110	0.122	0.080	0.137
Number of individuals	401,141	1,296,521	581,901	1,101,789	1,005,511
Four-digit results					
District, (ln) density of workers with the same two-digit occupation, ln	0.003**	0.002**	0.003**	0.002**	0.003**
	(0.000)	(0.000)	(0.001)	(0.000)	(0.000)
Neighbours, (ln) density of workers with the same two-digit occupation	0.000	−0.000	−0.001**	0.001**	−0.001**
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Region, (ln) density of workers with same two-digit occupation	0.004**	−0.003*	0.003	0.003*	−0.001
	(0.001)	(0.001)	(0.002)	(0.001)	(0.001)
District, (ln) density of workers with other occupations	−0.001	0.002**	0.005**	0.002**	0.004**
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
Neighbours, (ln) density of workers with other occupations	0.002**	0.001*	0.003**	−0.001**	0.002**
	(0.001)	(0.000)	(0.001)	(0.000)	(0.000)
Region, (ln) number of workers with other occupations	−0.009	0.043**	0.028**	0.025**	0.034**
	(0.008)	(0.003)	(0.005)	(0.005)	(0.003)
Number of observations	1,796,949	5,365,205	2,031,203	4,312,051	4,881,306
R^2 (within)	0.099	0.102	0.117	0.076	0.126
Number of individuals	367,960	1,235,481	544,524	1,030,944	946,236

Notes: Reported are the results from estimating equation (1) using more precise occupation groups, at the three- and four-digit levels, respectively. The regressions are otherwise estimated using the same variables as in Table 2. Other coefficients behave similarly to those of Table 2 and are omitted for brevity. All other variables (identical to those of Table 2) are omitted for brevity.
$^{**}p < 0.01$, $^{*}p < 0.05$.

aggregation, that is, two-digit, the density of same-occupation workers is statistically insignificant in manufacturing industries. As before, the density of other-occupation workers at the level of districts within cities is also statistically significant and positive, again except for manufacturing.

At the two-digit level, the estimated influences of neighbour- and region-level density of both same- and other-occupation workers are similar compared with Table 2. For the four-digit level, the main difference compared with Table 2 is that the number of same-occupation workers at the level of the wider region is negative and significant, although the effect size of the is negligible. We conclude that our baseline results concerning the influence on close proximity to workers in cities are not sensitive to the level of aggregation of occupational codes.

Other robustness tests: diversity indexes and cut-offs

We have also undertaken two additional tests of the robustness of the baseline results presented in Tables 1 and 2. First, with reference to the established literature on industrial specialization and diversity, we have run our main models with the inclusion of a diversity index

Table 4. Influence of the density of workers with the same and other occupations on the natural logarithm of wage income – panel fixed effects (FE) estimates for workers *outside* metropolitan regions.

	(1) Manufacturing	(2) Low-end services	(3) High-end services	(4) Routine skills	(5) Non-routine skills
District, (ln) density of workers with the	0.000	0.001**	0.001	0.001**	0.002**
same two-digit occupation	(0.000)	(0.000)	(0.001)	(0.000)	(0.000)
Neighbours, (ln) density of workers with	0.000*	0.000*	0.001*	0.000*	0.000**
the same two-digit occupation	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Region, (ln) density of workers with same	−0.000	0.001	0.004	0.001	−0.000
two-digit occupation	(0.001)	(0.001)	(0.002)	(0.001)	(0.001)
District, (ln) density of workers with other	−0.001*	−0.003**	−0.003*	−0.002**	−0.004**
occupations	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
Neighbours, (ln) density of workers with	−0.001	−0.001	0.000	−0.004**	−0.000
other occupations	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
Region, (ln) number of workers with	0.005*	0.001	−0.006	0.001	0.003
other occupations	(0.002)	(0.002)	(0.004)	(0.001)	(0.002)
District share university educated	0.031**	−0.035**	−0.024*	−0.038**	−0.019**
	(0.008)	(0.006)	(0.011)	(0.006)	(0.006)
Share university educated (neighbours)	0.006	−0.002	−0.031*	0.003	−0.008
	(0.008)	(0.007)	(0.016)	(0.007)	(0.008)
Age	0.029*	0.060	0.036**	0.059**	−0.166**
	(0.012)	(0.044)	(0.002)	(0.017)	(0.040)
Age squared	−0.000**	−0.000**	−0.001**	−0.000**	−0.001**
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
University education	0.282**	0.190**	0.260**	0.123**	0.273**
	(0.011)	(0.006)	(0.013)	(0.006)	(0.009)
Employer (ln) size	0.023**	0.011**	0.016**	0.018**	0.010**
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
Firm share university educated	0.059**	0.047**	0.041**	0.049**	0.044**
	(0.007)	(0.004)	(0.005)	(0.005)	(0.003)
Firm share same occupation	0.083**	0.050**	0.042**	0.071**	0.031**
	(0.002)	(0.001)	(0.003)	(0.001)	(0.002)
Capital (ln)	0.002**	0.004**	0.002**	0.004**	0.004**
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Mover	−0.019**	−0.027**	−0.005**	−0.036**	−0.002**
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
Constant	7.151**	6.258**	7.290**	6.195**	15.035**
	(0.443)	(1.518)	(0.187)	(0.576)	(1.505)
Number of observations	2,794,559	4,178,763	1,009,431	5,112,818	2,869,935
R^2 (within)	0.114	0.107	0.102	0.091	0.144
Number of individuals	524,350	929,993	286,337	1,067,614	591,735
Year FE	Yes	Yes	Yes	Yes	Yes
Occupation FE	Yes	Yes	Yes	Yes	Yes
Industry FE	Yes	Yes	Yes	Yes	Yes
Year × Industry FE	Yes	Yes	Yes	Yes	Yes

Notes: Reported are the results from estimating equation (1) for five different groups of workers. Models (1) to (3) present the results for workers based on the industry affiliation of the establishment at which they are employed. Models (4) and (5) present the results for workers based on the fraction non-routine tasks associated with their occupation. *Routine* is composed of workers with occupations involving job tasks of which fewer than 50% are classified as non-routine. *Non-routine* are workers with occupations involving job tasks of which 50% or more are classified as non-routine. The underlying data are employees in districts (1 km^2 squares) with at least 100 employees *outside* any of Sweden's main metropolitan regions, that is, Stockholm, Gothenburg or Malmo. Robust standard errors reported in parentheses.
**$p < 0.01$, *$p < 0.05$.

based on occupations.[10] The idea behind this is to test whether the density of other-occupation workers reflects density or if it is rather diversity that matters along the idea of Jacobs (1969). Second, we also test whether the main results are sensitive to the use of cut-offs. As explained in the data section, the empirical analysis is based on city districts (1 × 1 km squares) with at least 100 employees. To make sure that the main results are not dependent on this cut-off, we have also estimated the main models with no cut-offs at all. The results from these two additional tests of robustness are available from the authors upon request; they show that neither the inclusion of occupational diversity indexes nor changing cut-offs impact the main results.

Outside metropolitan regions

Our focus on metropolitan regions stems from the argument that skill bias in agglomeration economies primarily pertains to larger urban areas and cities. As argued in the introduction, there are several reasons to assess the estimated influence of the agglomeration variables on workers employed in districts outside large cities, which in a Swedish context implies outside the country's three main metropolitan regions (Stockholm, Gothenburg and Malmo).

Table 4 replicates the industry- and occupation-disaggregated results for workers in districts outside their main metropolitan regions. By comparing these results with those obtained for metropolitan regions (Table 2), we can gain an indication about whether any influence from our district-level variables is concentrated in metropolitan regions, or if our results support that these effects may be present in smaller regions as well.

Two things stand out in Table 4. First, the point estimates are low in almost every case. Second, and perhaps most notably, outside metropolitan regions we fail to find evidence pointing to the benefits of being close to other-occupation workers, irrespective of spatial level. Indeed, the estimated coefficient is often negative (with a possible exception for a small region effect in manufacturing). The findings are consistent with the finding that specialization is typically relatively more important in less dense regions than it is in dense city regions (cf. Groot et al., 2016), but it seems the majority share of any effects found in this paper is driven by metropolitan regions.

CONCLUSIONS

This paper has empirically analysed agglomeration gains between workers with similar skills, as evidenced by similar occupation, and assessed to what extent such agglomeration gains require close proximity. Based on a combination of the literature on attenuation of knowledge spillovers and the role of skills similarities in facilitating such spillovers, we developed two conjectures. First, knowledge spillovers are likely to operate at small spatial scales, such as city neighbourhoods or city districts. Second, effective knowledge spillovers require not only close geographical proximity, but also economic proximity (or relatedness). Drawing on Marshall's idea of similar 'skilled trades' we tested whether workers who operate near other workers with similar occupations within a city receive a productivity boost, as evidenced by higher wages.

Our main finding is that there is a robust and quantitatively important relationship between a worker's wage and the local density of workers in similar occupations in other firms. We also document evidence of an overall density effect, as evidenced by positive feedbacks between workers in *other occupations* and wages. We find only weak effects of overall density effects outside of the metropolitan areas. Our empirical context thus favours the argument that close spatial proximity *and* economic proximity (or relatedness) constitute fertile grounds for agglomeration effects. At the same time, such 'sub-city clusters' of workers with similar occupations appear to receive an extra boost by being in an overall dense and diversified city environment, up to and including the level of the full region. Although our empirical analysis cannot identify or discriminate between mechanisms, the overall results are consistent with the idea that close physical proximity within cities combined with skill similarity provide fertile grounds for knowledge spillovers that leave a footprint in workers' wages.

Policy-wise the results of this paper link up to recent arguments that local governments have great power to control agglomeration effects, because they seem to operate largely within the confines of cities (cf. Rosenthal & Strange, 2020). At this point, the evidence is mounting that agglomeration effects operate at small spatial scales, meaning that land-use planning policies within cities have potentially large influences on economic performance as they set the conditions for the sub-city organization of land and office space (Osman, 2020; Pan et al., 2021). By influencing the location pattern of firms within cities, such policies also influence the potential for various type of agglomeration externalities. For example, the employment density of districts in cities is directly related to the structure of buildings and transportation networks. Our analysis further points to the importance that land-use planning policy in cities is informed by the empirical literature on the attenuation, and nature, of agglomeration effects. The results do not imply that local policy should 'select' locations of firms and industries to try to create within-city clusters. However, they do provide one motivation for city planners to facilitate self-organized clusters at the sub-city level. Sound policy should allow a high density of, for example, office space where the market can bear it, and facilitate access to such clusters for workers throughout a city, for example, by investments in transportation networks.[11]

Our study is not free from limitations. We stress that the external validity of these results must be closely assessed in future research, but we maintain that the statistical association, as well as the meaningfulness of its size, in and of themselves are interesting inputs into further enquiry. The possibility that skill-biased clustering constitutes an important source of agglomeration gains is intriguing, but we are yet unable to demonstrate the underlying mechanisms. Moreover, there is certainly more work to be done before our results can be regarded as causal. Credible instrumentation and natural experiments are likely needed for that. It is possible that our results could be driven by time-variant unobservables at the level of cities or districts within cities that attract workers with similar occupations and at the same time increase wages. Future work could do more to try to address such identification challenges up front and pay greater attention to underlying mechanisms. The mysteries of the trade remain mysteries, perhaps, but Marshall's narrative stands strong.

There are at least two other areas of future research. First, our approach to occupation clustering could be cross-fertilized with studies of the labour force as vehicles for spillovers. Recent analyses on Swedish data show that mobility of workers does influence productivity of firms and that relatedness plays a central role in the patterns and consequences of job mobility (Falck et al., 2020; Kekezi, 2020). Against this backdrop, further analyses of these issues could explore the extent to which the effects identified in this paper could be explained by local patterns of inter-firm labour mobility and how such mobility relates to skill similarities.

Second, future studies should delve deeper into the actual meaning and interpretation of 'skills' and what type of similarity actually benefits from 'near neighborhood'. Detailed case studies and survey-based research of conscious and unconscious learning, network-building and motivation (including drive and 'grit') derived from working close to other people who are in some sense 'similar' would be welcomed in our view. Further, while we do maintain that occupation bins are an empirically feasible proxy, skill similarities can probably be conceptually better assessed through some more exact measure of the tasks involved in specific occupations. Future work could explore alternative ways to assess skill similarities, perhaps by drawing on established methods in the literature on relatedness, such as Neffke et al. (2017).

DISCLOSURE STATEMENT

No potential conflict of interest was reported by the authors.

NOTES

1. In addition to knowledge spillovers (or learning), the forces of agglomeration economies also include sharing and matching (e.g., Duranton & Puga, 2004). Sharing of resources, such as a wide variety of input suppliers that can support many different production industries, typically extend across rather large distances. Matching effects on labour markets are generally assumed to operate within commuting areas, which in turn often involve commuting time-distances of around one hour (Johansson et al., 2002). Empirical analyses also confirm that knowledge spillovers appear to be more local than effects arising from sharing labour and inputs (Ellison et al., 2010).

2. The idea that effective knowledge spillovers require relatedness may be perceived of as being in contrast to Jane Jacobs' notion of cross-industry spillovers (Jacobs, 1969), as well as work on the diversity for so-called recombinant innovation (e.g., Frenken et al., 2012). First, our focus on similarities in skills does not imply that cross-industry spillovers are irrelevant as workers with similar occupations may work in different industries. Second, the work on recombinant innovation emphasizes that variety is important for more radical innovations, while combinations of more similar technologies or ideas are more prone to generate less radical innovation. Our work does not focus on innovation. Instead, we focus on productivity.

3. One exception is Larsson (2014) who uses geocoded employer–employee panel data to assess agglomeration effects at different spatial scales in Sweden. The present study further contributes with an analysis of skill similarities, linking up with Marshall's (1920) original assertion.

4. Excluded workers are only excluded from the regressions; they counted towards the density measures and other right-hand-side variables.

5. See https://www.ilo.org/public/english/bureau/stat/isco/isco88/index.htm.

6. The issue of geographical borders arises in any empirical context of agglomeration economies. In principle there is a trade-off. Larger geographical units alleviate issues of overlap across borders, but are at the same time not suitable to identify externalities operating at small spatial scales. Small geographical units are preferable to identify externality effects at small scales, but could bring questions about possible overlaps. Given the purpose of this paper, we choose to use small spatial scales (1 × 1 km squares), but also use neighbours and the level of the wider city.

7. We are not allowed to extract data in cases where there is a risk that individual firms or persons may be identified.

8. At the level of districts, the uniform 1 km^2 square grid implies that the number of employees in a district, as well as in neighbours, is an exact measure of employment density per km^2.

9. Becker et al. (2013) classify answers in a German qualification and career survey for 1998/99, undertaken by the German Federal Institute for Vocational Training and the research institute of the German Federal Labour Agency. The survey tracks the usage of 81 different tools in a multitude of occupations. Different tools are classified according to their relation to non-routine tasks (non-repetitive work methods). The different tasks are then mapped to ISCO-88 standardized occupations. For each occupation, the degree of non-routine tasks is then computed as the ratio between the average number of non-routine tasks in the occupation and the maximum number in any occupation, and the numbers are then standardized so that the fraction of non-routine tasks in an occupation varies between 0 and 1.

10. We employed an inverted Herfindahl index, following Martin et al. (2011).

11. Recent evaluations of city cluster programmes show that cluster policy, such as business support, tax breaks,

place-branding and network-building elements, appears to have limited effects. An analysis of the so-called Tech-City programme in London by Nathan (2020) shows precisely that the cluster policy had at best weak effects and that the growth of the firms had to do with processes that started long before the policy was in place. What we mean here is policy that facilitates the emergence of self-organized clustering rather than cluster policy that directly aims to 'create' or 'manage' clusters.

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REFERENCES

Ahlin, L., Andersson, M., & Thulin, P. (2018). Human capital sorting: The 'when' and 'who' of the sorting of educated workers to urban regions. *Journal of Regional Science*, *58*(3), 581–610. https://doi.org/10.1111/jors.12366

Andersson, M., Klaesson, J., & Larsson, J. P. (2014). The sources of the urban wage premium by worker skills: Spatial sorting or agglomeration economies? *Papers in Regional Science*, *93*(4), 727–747. https://doi.org/10.1111/pirs.12025

Andersson, M., Klaesson, J., & Larsson, J. P. (2016). How local are spatial density externalities? Neighbourhood effects in agglomeration economies. *Regional Studies*, *50*(6), 1082–1095. https://doi.org/10.1080/00343404.2014.968119

Andersson, M., Larsson, J. P., & Wernberg, J. (2019). The economic microgeography of diversity and specialization externalities: Firm-level evidence from Swedish cities. *Research Policy*, *48*(6), 1385–1398. https://doi.org/10.1016/j.respol.2019.02.003

Arzaghi, M., & Henderson, J. V. (2008). Networking off Madison avenue. *The Review of Economic Studies*, *75*(4), 1011–1038. https://doi.org/10.1111/j.1467-937X.2008.00499.x

Autor, D. H. (2019). Work of the past, work of the future. *American Economic Association – Papers and Proceedings*, *109*(1), 1–32. https://doi.org/10.1257/aer.20171019

Autor, D. H., Levy, F., & Murnane, R. J. (2003). The skill content of recent technological change: An empirical exploration. *The Quarterly Journal of Economics*, *118*(4), 1279–1333. https://doi.org/10.1162/003355303322552801

Bacolod, M., Blum, B. S., & Strange, W. C. (2009). Skills in the city. *Journal of Urban Economics*, *65*(2), 136–153. https://doi.org/10.1016/j.jue.2008.09.003

Baldwin, R. (2016). *The great convergence*. Harvard University Press.

Baum-Snow, N., Freedman, M., & Pavan, R. (2018). Why has urban inequality increased? *American Economic Journal: Applied Economics*, *10*(4), 1–42. https://doi.org/10.1257/app.20160510

Beaudry, C., & Schiffauerova, A. (2009). Who's right, Marshall or Jacobs? The localization versus urbanization debate. *Research Policy*, *38*(2), 318–337. https://doi.org/10.1016/j.respol.2008.11.010

Bechky, B. A. (2003). Sharing meaning across occupational communities: The transformation of understanding on a production floor. *Organization Science*, *14*(3), 312–330. https://doi.org/10.1287/orsc.14.3.312.15162

Becker, S. O., Ekholm, K., & Muendler, M. A. (2013). Offshoring and the onshore composition of tasks and skills. *Journal of International Economics*, *90*(1), 91–106. https://doi.org/10.1016/j.jinteco.2012.10.005

Boschma, R. (2005). Proximity and innovation: A critical assessment. *Regional Studies*, *39*(1), 61–74. https://doi.org/10.1080/0034340052000320887

Boschma, R., Balland, P. A., & Kogler, D. F. (2015). Relatedness and technological change in cities: The rise and fall of technological knowledge in US metropolitan areas from 1981 to 2010. *Industrial and Corporate Change*, *24*(1), 223–250. https://doi.org/10.1093/icc/dtu012

Carrincazeaux, C., Lung, Y., & Vicente, J. (2008). The scientific trajectory of the French School of proximity: Interaction- and institution-based approaches to regional innovation systems. *European Planning Studies*, *16*(5), 617–628. https://doi.org/10.1080/09654310802049117

Cheshire, P. C., Nathan, M., & Overman, H. G. (2014). *Urban economics and urban policy: Challenging conventional policy wisdom*. Edward Elgar.

Cohen, W. M., & Levinthal, D. A. (1990). Absorptive capacity: A new perspective on learning and innovation. *Administrative Science Quarterly*, *35*, 128–152. https://doi.org/10.2307/2393553

Combes, P. P., Duranton, G., & Gobillon, L. (2008). Spatial wage disparities: Sorting matters! *Journal of Urban Economics*, *63*(2), 723–742. https://doi.org/10.1016/j.jue.2007.04.004

Desrochers, P., & Leppälä, S. (2011). Opening up the 'Jacobs spillovers' black box: Local diversity, creativity and the processes underlying new combinations. *Journal of Economic Geography*, *11*(5), 843–863. https://doi.org/10.1093/jeg/lbq028

Duranton, G., & Puga, D. (2001). Nursery cities: Urban diversity, process innovation, and the life cycle of products. *American Economic Review*, *91*(5), 1454–1477. https://doi.org/10.1257/aer.91.5.1454

Duranton, G., & Puga, D. (2004). Micro-foundations of urban agglomeration economies. In V. Henderson & J.-F. Thisse (Eds.), *Handbook of regional and urban economics* (Vol. 4, pp. 2063–2117). North Holland.

Duranton, G., & Puga, D. (2005). From sectoral to functional urban specialization. *Journal of Urban Economics*, *57*(2), 343–370. https://doi.org/10.1016/j.jue.2004.12.002

Ellison, G., Glaeser, E. L., & Kerr, W. R. (2010). What causes industry agglomeration? Evidence from coagglomeration patterns. *American Economic Review*, *100*(3), 1195–1213. https://doi.org/10.1257/aer.100.3.1195

Faggio, G., Silva, O., & Strange, W. C. (2017). Heterogeneous agglomeration. *Review of Economics and Statistics*, *99*(1), 80–94. https://doi.org/10.1162/REST_a_00604

Falck, S., Mattsson, P., & Westlund, H. (2020). *Productivity effects of knowledge transfers through inter-firm labour mobility* (Tillväxtanalys Working Paper No. 2020:03). https://www.tillvaxtanalys.se/download/18.1235fa2a173481d283cbe73b/1599468351956/wp_2020_03_Productivity%20effects%20of%20knowledge%20transfers%20through%20inter-firm%20labour%20mobility.pdf

Feldman, M. P., & Audretsch, D. B. (1999). Innovation in cities: Science-based diversity, specialization and localized competition. *European Economic Review*, *43*(2), 409–429. https://doi.org/10.1016/S0014-2921(98)00047-6

Frenken, K., Izquierdo, L. R., & Zeppini, P. (2012). Branching innovation, recombinant innovation, and endogenous technological transitions. *Environmental Innovation and Societal Transitions*, *4*, 25–35. https://doi.org/10.1016/j.eist.2012.06.001

Frenken, K., Van Oort, F., & Verburg, T. (2007). Related variety, unrelated variety and regional economic growth. *Regional Studies*, *41*(5), 685–697. https://doi.org/10.1080/00343400601120296

Gathmann, C., & Schönberg, U. (2010). How general is human capital? A task-based approach. *Journal of Labor Economics*, *28*(1), 1–49. https://doi.org/10.1086/649786

Gilly, J. P., & Torre, A. (2000). Proximity relations. Elements for an analytical framework. In *Industrial networks and proximity* (pp. 1–16).

Glaeser, E. L., & Kohlhase, J. E. (2003). Cities, regions and the decline of transport costs. *Papers in Regional Science*, *83*(1), 197–228. https://doi.org/10.1007/s10110-003-0183-x

Glaeser, E. L., & Resseger, M. G. (2010). The complementarity between cities and skills. *Journal of Regional Science*, *50*(1), 221–244. https://doi.org/10.1111/j.1467-9787.2009.00635.x

Greenstone, M., Hornbeck, R., & Moretti, E. (2010). Identifying agglomeration spillovers: Evidence from winners and losers of large plant openings. *Journal of Political Economy*, *118*(3), 536–598. https://doi.org/10.1086/653714

Groot, H. L., Poot, J., & Smit, M. J. (2016). Which agglomeration externalities matter most and why? *Journal of Economic Surveys*, *30*(4), 756–782. https://doi.org/10.1111/joes.12112

Hidalgo, C. A., Balland, P. A., Boschma, R., Delgado, M., Feldman, M., Frenken, K., & Neffke, F. (2018, July). The principle of relatedness. In *International conference on Complex Systems* (pp. 451–457). Springer.

Jacobs, J. (1969). *The economy of cities*. Vintage.

Johansson, B., Klaesson, J., & Olsson, M. (2002). Time distances and labor market integration. *Papers in Regional Science*, *81*(3), 305–327. https://doi.org/10.1007/s101100200000

Kambourov, G., & Manovskii, I. (2009). Occupational specificity of human capital. *International Economic Review*, *50*(1), 63–115. https://doi.org/10.1111/j.1468-2354.2008.00524.x

Kekezi, O. (2020). *Labor mobility across jobs and space* [Doctoral dissertation]. Jönköping University, Jönköping International Business School. http://hj.diva-portal.org/smash/record.jsf?faces-redirect=true&aq2=%5B%5B%5D%5D&af=%5B%5D&searchType=SIMPLE&sortOrder2=title_sort_asc&query=&language=sv&pid=diva2%3A1430571&aq=%5B%5B%5D%5D&sf=all&aqe=%5B%5D&sortOrder=author_sort_asc&onlyFullText=false&noOfRows=50&dswid=-9566

Kemeny, T., & Storper, M. (2015). Is specialization good for regional economic development? *Regional Studies*, *49*(6), 1003–1018. https://doi.org/10.1080/00343404.2014.899691

Larsson, J. P. (2014). The neighborhood or the region? Reassessing the density–wage relationship using geocoded data. *The Annals of Regional Science*, *52*(2), 367–384. https://doi.org/10.1007/s00168-014-0590-8

Lavoratori, K., & Castellani, D. (2021). Too close for comfort? Microgeography of agglomeration economies in the United Kingdom. *Journal of Regional Science*. https://doi.org/10.1111/jors.12531

Marrocu, E., Paci, R., & Usai, S. (2013). Productivity growth in the old and new Europe: The role of agglomeration externalities. *Journal of Regional Science*, *53*(3), 418–442. https://doi.org/10.1111/jors.12000

Marshall, A. (1920). *Principles of economics* (8th ed). Macmillan.

Martin, P., Mayer, T., & Mayneris, F. (2011). Spatial concentration and plant-level productivity in France. *Journal of Urban Economics*, *69*(2), 182–195. https://doi.org/10.1016/j.jue.2010.09.002

Michaels, G., Rauch, F., & Redding, S. J. (2019). Task specialization in U.S. Cities from 1880 to 2000. *Journal of the European Economic Association*, *17*(3), 754–798. https://doi.org/10.1093/jeea/jvy007

Moretti, E. (2004). Workers' education, spillovers, and productivity: Evidence from plant-level production functions. *American Economic Review*, *94*(3), 656–690. https://doi.org/10.1257/0002828041464623

Nathan, M. (2020). Does light touch cluster policy work? Evaluating the tech city programme. *Research Policy*, 104138. https://doi.org/10.1016/j.respol.2020.104138

Neffke, F., & Henning, M. (2013). Skill relatedness and firm diversification. *Strategic Management Journal*, *34*(3), 297–316. https://doi.org/10.1002/smj.2014

Neffke, F., Henning, M., & Boschma, R. (2011). How do regions diversify over time? Industry relatedness and the development of new growth paths in regions. *Economic Geography*, *87*(3), 237–265. https://doi.org/10.1111/j.1944-8287.2011.01121.x

Neffke, F. M., Otto, A., & Weyh, A. (2017). Inter-industry labor flows. *Journal of Economic Behavior & Organization*, *142*, 275–292. https://doi.org/10.1016/j.jebo.2017.07.003

Nooteboom, B. (2000). *Learning and innovation in organizations and economies*. Oxford University Press.

Osman, T. (2020). Restrictive land use regulations and economic performance. *International Regional Science Review*, *43*(4), 291-315.

Pan, H., Yang, T., Jin, Y., Dall'Erba, S., & Hewings, G. (2021). Understanding heterogeneous spatial production externalities as a missing link between land-use planning and urban economic futures. *Regional Studies*, *55*(1), 90-100.

Parr, J. B. (2002). Agglomeration economies: Ambiguities and confusions. *Environment and Planning A: Economy and Space*, *34*(4), 717–731. https://doi.org/10.1068/a34106

Rauch, J. (1993). Productivity gains from geographic concentration of human capital: Evidence from the cities. *Journal of Urban Economics*, *34*(3), 380–400. https://doi.org/10.1006/juec.1993.1042

Rigby, D. L. (2015). Technological relatedness and knowledge space: Entry and exit of US cities from patent classes. *Regional Studies*, *49*(11), 1922–1937. https://doi.org/10.1080/00343404.2013.854878

Rodríguez-Pose, A., & Storper, M. (2020). Housing, urban growth and inequalities: The limits to deregulation and upzoning in reducing economic and spatial inequality. *Urban Studies*, *57*(2), 223–248.

Rosenthal, S. S., & Strange, W. C. (2003). Geography, industrial organization, and agglomeration. *Review of Economics and Statistics*, *85*(2), 377–393. https://doi.org/10.1162/003465303765299882

Rosenthal, S. S., & Strange, W. C. (2008). The attenuation of human capital spillovers. *Journal of Urban Economics*, *64*(2), 373–389. https://doi.org/10.1016/j.jue.2008.02.006

Rosenthal, S. S., & Strange, W. C. (2020). How close is close? The spatial reach of agglomeration economies. *Journal of Economic Perspectives*, *34*(3), 27–49. https://doi.org/10.1257/jep.34.3.27

Spitz-Oener, A. (2006). Technical change, job tasks and rising educational demands: Looking outside the wage structure. *Journal of Labor Economics*, *24*(2), 235–270. https://doi.org/10.1086/499972

Torre, A., & Rallet, A. (2005). Proximity and localization. *Regional Studies*, *39*(1), 47–59. https://doi.org/10.1080/0034340052000320842

Williamson, O. E. (1985). *The economic institutions of capitalism: Firms, markets, relational contracting*. Free Press.

Wixe, S., & Andersson, M. (2017). Which types of relatedness matter in regional growth? Industry, occupation and education. *Regional Studies*, *51*(4), 523–536. https://doi.org/10.1080/00343404.2015.1112369

Xiao, J., Boschma, R., & Andersson, M. (2018). Industrial diversification in Europe: The differentiated role of relatedness. *Economic Geography*, *94*(5), 514–549. https://doi.org/10.1080/00130095.2018.1444989