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Mysteries of the Trade? Skill-Specific Local Agglomeration Economies

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Mysteries of the trade?

Skill-specific local agglomeration economies

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Abstract

Using longitudinal Swedish data, we document robust evidence of highly local spillovers between individuals in similar occupations. The results are consistent with the existence of knowledge spillovers between workers performing similar work tasks in the same city-district. We further demonstrate less distance-sensitive benefits of working in diverse districts and regions, characterized by high density of employees in other occupations. The diversity benefits exist only in metropolitan areas and pertain to workers performing advanced services or non-routine work tasks.

JEL Codes: R10, R12, J24

Keywords: agglomeration economies, wages, spillovers, attenuation, clusters, economic proximity, relatedness

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1. INTRODUCTION

Alfred Marshall's (1920) paragraph about how *“the mysteries of the trade become no mysteries”* through knowledge *“in the air”* may well be one of the most exhausted quotes in the regional sciences. Yet, it has often come to represent knowledge spillovers in general, rather than those spillovers between 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.

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 have shifted towards a greater emphasis on contexts in which knowledge, technology and interactions between workers as well as firms are important (Glaeser and Kohlhase 2004). 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 location in agglomerations.

One stream of literature shows that ’economies of density’ primarily pertain to knowledge-intensive workers and tasks intensive in interaction (Bacolod, Blum and Strange 2009; Glaeser and Resseger 2010; Andersson, Klaesson and Larsson 2014). Another stream studies patterns of specialization across cities and find 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 and Puga 2005). Studies of the long-run development of the occupational structure of cities in the US further show that the employment share of occupations associated with interactivity have increased at faster pace in metropolitan areas compared to other places (Michaels, Rauch and Redding 2018). Baum-Snow, Freedman and Pavan (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 a 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, Levy and Murnane 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, Nathan and Overman 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 whether they depend similarities in occupation, industry or technology, or if they diffuse with little friction across such boundaries.

In this paper, we provide new empirical evidence on these issues by analyzing how wage gains from working in dense city districts within metropolitan areas depend on skill similarities, as evidenced by occupational domains. We thus draw on Marshall's ideas on benefits of a local density of workers with similar skilled trade and estimate wage gains from close proximity to workers with similar occupations. We employ matched employer-employee panel data and estimate Mincerian wage equations to assess whether agglomeration economies are contingent on skill similarities, as evidenced by workers' occupational belonging.

1.1 Background and contribution

Our paper relates to two main strands of literature. First, the literature on the geography and attenuation of agglomeration economies and second, the literature on the role of economic proximity (or relatedness) in facilitating spillover effects between firms as well as workers. A main finding from the first set of studies is that there are significant agglomeration effects operating at small spatial scales inside cities, confined to sub-city districts or neighborhoods (Arzaghi and Henderson 2008; Rosenthal and Strange 2003, 2008; Andersson, Larsson and Wernberg 2019; Larsson 2014; Lavoratori and Castellani 2020). This type of localized agglomeration effect is typically assumed to reflect some kind of knowledge spillovers, since they are more likely to require close proximity and thus prone to operate at finer spatial scales than other forces that generate agglomeration economies (Arzaghi and Henderson, 2008; Rosenthal and Strange 2019).[1]

If the sources of agglomeration gains have shifted towards a more important role for knowledge spillovers, then the importance of close proximity may have grown over time as cities increasingly specialize in knowledge- and interaction-intensive activities. This shift implies a need for granular data to identify and assess knowledge spillovers. To this end, we make use of finely geo-coded data and an exogenous partition of cities in Sweden based on a grid of one-by-one km squares. The

[1] In addition to knowledge spillovers (or learning), the forces of agglomeration economies also include sharing and matching (see e.g. Duranton and 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 labor markets are generally assumed to operate within commuting areas, which in turn often involve commuting time-distances of around one hour (Johansson, Klaesson and Olsson 2002). Empirical analyses also confirm that knowledge spillovers appear to be more local than effects arising from sharing labor and inputs (Ellison, Glaeser and Kerr 2010).

detailed geo-coding 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.

The second strand of literature to which we contribute analyzes the role of economic proximity (or relatedness), and highlights that geographic proximity is not enough to generate productive spillovers. Instead, it is a combination of geographic proximity and some form of economic proximity with regards to similarity in knowledge bases, skills, technology or industry that drives productive spillovers (Boschma 2005; Frenken, van Oort and Verburg 2007; Hidalgo et al 2018). Conceptually, this line of argument is based on several different schools of thought, such as the role of absorptive capacity for efficient transmission of knowledge (Cohen and Levinthal 1990), the so-called 'French school of proximity' that emphasizes various dimensions of proximity (Gilly and Torre 2000; Torre and Rallet 2005; Carrincazeaux, Lung and Vicente 2008) as well as the idea that the balance between cognitive proximity and distance matters for spillovers and learning (Nooteboom 2000; Boschma 2005). 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 geographic *and* economic proximity between firms as well as between workers (Moretti 2004b; Greenstone, Hornbeck and Moretti 2010). There is also evidence that a variety of related industries in a region boosts employment growth (Frenken, van Oort and Verburg 2007; Wixe and Andersson 2017), and that relatedness between technologies and skills boosts the development of new specializations in cities and regions (Neffke, Henning and Boschma 2011; Rigby 2015; Boschma, Balland and Kogler 2015; Xiao, Boschma and Andersson 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 (see e.g. Moretti 2004, Neffke and Henning 2013).

We assess the role of economic proximity by analyzing whether estimates of spillover effects from close geographic proximity to other workers is conditional on skill similarities, as evidenced by occupational domains. Rather than focusing on industry belonging, we follow Marshall's (1920) original idea of the relevance of skilled trades and focus on the broad occupational tasks that workers perform in firms and organizations. The rationale is that similar occupational domains imply that workers, although employed in different industries and organizations, have similar tasks and functions in their respective organizations. 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 constitute a relevant context for acquiring experiences and skills.[2] For example, it is easy to imagine that managers and marketing professionals can learn, copy behaviors from each other or exchange information and experiences on issues of workforce management and marketing strategies, respectively, although they come from 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 that develop software in a car manufacturing company.[3] There is also empirical evidence suggesting that relevant human capital appears to be occupation-specific, rather than industry- or firm-specific (Gathmann and Schönberg 2010; Kambourov and 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 he or she keeps 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.

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, Larsson and Wernberg 2019). The attenuation literature has focused on empirically assessing the distance-decay of localization and urbanization effects as well as of human capital spillovers (e.g. Rosenthal and Strange 2008; Arzaghi and Henderson 2008; Andersson, Klaesson and Larsson 2016; Lavoratori and Castellani 2020) with little attention paid to the influence of various forms of economic proximity beyond industry domains. 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, van Oort and Verburg 2007, Rigby 2015; Neffke, Henning and Boschma 2011), which implies that agglomeration effects operating at small spatial scales cannot be identified and assessed. Furthermore, the bulk of empirical analyses in both literatures have either used industry-region data or firm-level data and focused on outcomes such as employment growth, productivity, average wages and birth of new establishments. Even though individual workers are key 'agents' in the context of spillovers, few analyses in this

[2]As an example, 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 (see 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, as captured by occupation domain.

[3] See Desrochers and Leppälä (2011) for more examples and discussions along these lines.

vein have employed individual employee-level data to assess either the geography of agglomeration effects or the influence of economic proximity or relatedness.[4]

We contribute with an empirical analysis using geo-coded matched employer-employee panel data that allow us to account for the fact that agglomeration gains may operate at small spatial scales and also account for the role of economic proximity by analyzing if effects at various spatial levels are influenced by skill similarity. Thereby, we provide novel empirical evidence of relevance to both types of literatures.

We employ geo-coded matched employer-employee data on workers in Swedish cities from 2002 to 2013 and 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 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 number of workers outside the own workplace, the size of which we also control for. Both types of variables are computed at three spatial levels: (i) the within-city district (a one-by-one km square), (ii) first-order neighbors, i.e. eight neighbor squares, and iii) the labor market region. We hence assess whether evidence of effects operates at different scales, and thereby whether it attenuates across different levels. To test the argument that the role of agglomeration effects matters more for knowledge- and interaction-intensive occupations (Bacolod, Blum and Strange 2009; Andersson, Klaesson and Larsson 2014), 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 high density of workers with the same occupation. In advanced services and in non-routine professions we also find evidence of benefits of being in proximity to workers in *other* occupations. This latter effect appears to be less distance sensitive. 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 diverse surroundings.

[4] One exception is Larsson (2014) who uses geo-coded employer-employee panel data to assess agglomeration effects at different spatial scales in Sweden.

2. DATA

2.1 Matched employer-employee panel data

We employ geocoded matched employee-employer panel for Sweden spanning 12 years (2002-2013). 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 the month of 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. 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. The occupational coding is based on 2-digit International Standard Classification of Occupations (ISCO-88).

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.

2.2 Geo-coding: one-by-one km squares

Each establishment is associated with a geocoded cell in a country-wide grid of one-by-one km squares. We refer to these squares as city-districts. The geo-coding is exogenous because the size as well as position of the squares are independent of underlying economic activity. Many standard geographic 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 (Arzaghi and Henderson 2008; Rosenthal and Strange 2008; Andersson, Larsson and Wernberg 2019).

The underlying "true" scale of agglomeration effects could of course cover several squares.[5] By construction of the grid, each district, *d,* has eight first-order neighbors as in Figure 1. In the analysis, variation at the sub-regional scale is captured at the level of districts and at the level of first-order neighbors. By including districts as well as first-order neighbors, we test for 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 neighboring districts, *n(d).*

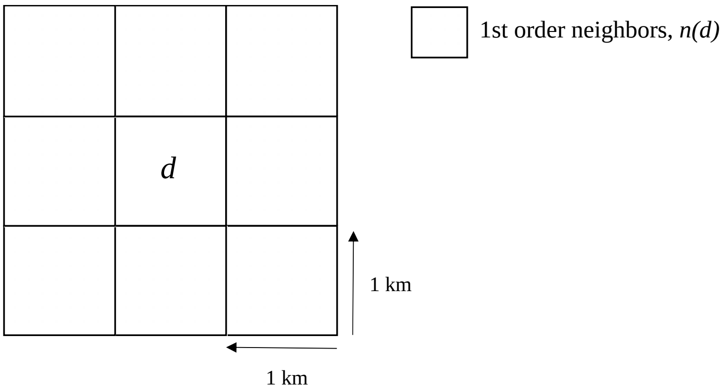

Figure 1. *Squares and neighbors.*

We run our baseline models for all workers in Sweden's main metropolitan areas, i.e. Stockholm, Gothenburg and Malmö, and focus the analysis on districts with at least 100 employees outside the own work establishment. We impose this cutoff in part for integrity reasons[6] and in part to ensure that minor events do not impact our results. We do note that all results presented are insensitive to moving the cutoff up or down. With these restrictions, our main dataset contains about 2 million metropolitan employees observed over a total of 11.3 million individual-years.

[5]The issue of geographic borders arises in any empirical context of agglomeration economies. In principle there is a tradeoff. Larger geographic units alleviate issues of overlap across borders but are at the same time not suitable to identify externalities operating at small spatial scales. Small geographic units are preferable in order 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 (one-by-one km squares), but also use neighbors and the level of the wider city.
[6]We are not allowed to extract data in cases where there is a meaningful risk that individual firms or persons may be identified

3. MODEL AND ESTIMATION

3.1 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.

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

where $w_{i,o,d,t}$ is the wage of worker *i* with occupation *o* working in district *d* in year *t*. **X** is a vector of worker- and employer-level control variables. For individual workers it includes age, age squared, and a dummy equal to one if the worker has a long university education ($\geq$ 3 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 2-digit industry (NACE) in which the establishment is classified. 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 one 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 2-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 fixed effects imply that the industry and occupation dummy variables are identified solely on workers who move between different industries and change occupations. The fixed effects imply that a change in district employment can come about in two ways: (i) the worker moves his or her place of work from one district to another, or (ii) 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 the own work establishment. A main goal is to assess if benefits of close geographic proximity to other workers is conditional on skill similarities, as evidence by occupational domains. To this end, we develop two different agglomeration measures defined at three contiguous spatial scales. The first variable is $OC\_same_{o,d,t}^{district}$, which measures the number of employees working in the same district and in the same 2-digit occupation as worker *i*. Formally:

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

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 the own place of work. This is the local density of workers with the same 2-digit occupation as a worker in a district (1 km square) and is intended to reflect the potential for productive spillovers between workers in different organizations, but active within a similar occupational domain.[7] Note that this measure is different for two workers that 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 that 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 neighbor districts (see Figure 1):

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

where $EMP_{o,n(d),t}$ refers to the sum of the number of employees with occupation *o* in the eight neighbor squares of district *d*, *n(d)*. By including both measures as separate variables, we analyze 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:

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

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 the own establishment is given by the total number of other-occupation workers outside the own workplace:

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

where $EMP_{d,t}$ is the total number of employees in district *d*. The same variable at the level of 1st order neighbors *n*(*d*) is given by:

[7]Note that 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 neighbors, is an exact measure of employment density per km^2.

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

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:

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

We further include the fraction of the total number of employees with a long university education ($\geq$ 3 years) at the district and neighboring districts, respectively. Several empirical analyses of human capital spillovers at the regional level document that local density of educated workers influence worker wages as well as productivity of plants (Rauch 1993, Moretti 2004ab). We therefore include the human capital in districts, $HC^{district}_{d,t}$, and neighbor districts, $HC^{neighbors}_{n(d),t}$, as control variables. These are defined as follows:

(9a) $$HC^{district}_{d,t} = \frac{EMP^{edu}_{d,t}}{EMP_{d,t}}$$

(9b) $$HC^{neighbors}_{n(d),t} = \frac{EMP^{edu}_{n(d),t}}{EMP_{n(d),t}}$$

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

All variables are summarized in the descriptive Table A1.

3.1 Estimates for sub-groups of workers

After estimating our model for all workers, we exploit the richness of the data to explore results for different sub-groups of workers. A large empirical literature documents that the influence of agglomeration characteristics is heterogenous and industry-dependent (Faggio, Silva and Strange 2017; Groot, Poot and Smit 2016) as well as the type of job and worker (Bacolod, Blum and Strange 2009; Andersson, Klaesson and Larsson 2014; Autor 2019). A consistent finding in the previous literature analyzing skill-biases in regional data is that agglomeration gains are driven by high-tech and more knowledge-intensive industries as well as for highly educated workers and workers with job tasks associated with social interactions, problem solving and creativity. Here, we assess this issue in an intra-city analysis.

We estimate our models for two different sub-groupings of workers. First, we run models for workers by broad industry classifications. We separate between workers employed in manufacturing, low-end services and high-end services. Low-end services comprise basic services like wholesale and retail trade whereas high-end services include knowledge-intensive services, such as 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 beloging. Similar to Andersson et al (2014), we make use of a job-task classification scheme developed by Becker, Ekholm and Muendler (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, Ekholm and Muendler (2013) is similar to that of Autor, Levy and Murnane (2003) and Spitz-Oener (2006) in that occupations are linked to the involved share of routine vs. non-routine tasks.[8] We use these data to estimate models for workers with occupations involving high (50 percent or more) and low (less than 50 percent) fractions of non-routine tasks, respectively. The literature on the skill-bias in agglomeration economies suggest that local agglomeration should matter more for knowledge-intensive industries and educated workers, as well as for workers having jobs with higher fractions of non-routine job tasks.

4. RESULTS

4.1 Metropolitan regions

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). Then estimate the model with district-level variables only (column 2), then with first-order neighbors (3), then with regional level-variables (4). Column (5) presents the complete model estimated with OLS model in levels (without

[8]Becker, Ekholm and Muendler (2013) classify answers in a German qualification and career survey for 1998/1999, undertaken by the German Federal Institute for Vocational Training and the research institute of the German Federal Labour Agency. It 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.

the individual-level fixed effects, λ_i) for reference. As a further reference, Table A2 in Appendix presents specifications 2-4 estimated with OLS.

Table 1. The influence of density of workers with the same and other occupations on the wage income of workers, INSIDE metropolitan regions.

	(1) Panel, FE	(2) Panel, FE	(3) Panel, FE	(4) Panel, FE	(5) OLS
District, density of workers with the same 2-digit occupation, ln)	0.007**	0.007**			0.017**
	(0.000)	(0.000)			(0.000)
Neighbors, density of workers with the same 2-digit occupation, ln	0.000**		0.000**		0.000**
	(0.000)		(0.000)		(0.000)
Region, density of workers with same 2-digit occupation, ln	0.022**			0.030**	0.022**
	(0.002)			(0.002)	(0.001)
District, density of workers with other occupations, ln	0.001	0.000			0.002**
	(0.000)	(0.000)			(0.000)
Neighbors, density of workers with other occupations, ln	-0.000		0.003**		-0.000
	(0.000)		(0.000)		(0.000)
Region, density of workers with other occupations, ln	0.011**			-0.003	0.014**
	(0.003)			(0.003)	(0.001)
Share university educated (district)	-0.015**	-0.015**	0.003	0.008**	0.001
	(0.003)	(0.003)	(0.003)	(0.003)	(0.002)
Share university educated (1st order neighbors)	-0.014**	-0.014**	-0.012**	0.004	-0.023**
	(0.004)	(0.004)	(0.004)	(0.004)	(0.002)
Age	0.043*	0.042*	0.042*	0.043*	0.053**
	(0.019)	(0.018)	(0.018)	(0.019)	(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	0.280**	0.281**	0.281**	0.281**	0.074**
	(0.003)	(0.003)	(0.003)	(0.003)	(0.001)
Employer size (log)	0.009**	0.009**	0.009**	0.009**	0.014**
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Capital (ln)	0.005**	0.005**	0.005**	0.005**	0.053**
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Mover	-0.021**	-0.021**	-0.021**	-0.022**	-0.064**
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Year FE	YES	YES	YES	YES	YES
SSYK FE	YES	YES	YES	YES	YES
SNI FE	YES	YES	YES	YES	YES
YEARxSNI FE	YES	YES	YES	YES	YES
# of observations	11,328,883	11,328,883	11,328,883	11,328,883	11,328,883
# of workers	2,039,379	2,039,379	2,039,379	2,039,379	2,039,379
R-squared	0.128	0.128	0.128	0.128	0.346

Note: The table reports results from an estimation of the model in equation (1) for with different specifications. Model 1 includes all variables. Model 2 only includes the district level, model 3 only the neighborhood level and model 4 only the region level as regards our variables of main interest. As a reference, Model 5 estimates the model with all variables using OLS. In models 1-4, all parameters are estimated with a panel estimator with worker-level fixed effects. The underlying data are employees in districts (1 km squares) with at least 100 employees within any of Sweden's main metropolitan regions, i.e. Stockholm, Gothenburg or Malmö local labor market regions. Robust standard errors reported within brackets. *** p<0.01, ** p<0.05, * p<0.1.

The fully specified model with FE in column (1) informs that doubling of local density of same-occupation workers is associated with a wage increase of 0.7%. This is a lower point estimate compared to those pertaining to the regional-level variables, but for a variable with much higher underlying variability. One way of appreciating the meaningfulness of the result is that “doubling 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 1A, a one standard-deviation increase in the number of same-occupation workers in the “average” district will increase that occupation’s local density by more than 200 percent, and a one within-standard deviation represents more than a doubling. For first-degree neighboring district variables, the ratios of standard deviations to averages are further magnified. These figures should be compared to the region level variables where the standard deviations 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 neighboring squares is positive and statistically different from zero, but of modest economic significance. Looking at columns 2-4 in the table, we also see that the main results are insensitive to alternative specifications. In particular, there appear to be a highly local effect of density of workers with the same occupation which is not picked-up at the level of neighbors when the district level is excluded (see column 3).

Any positive statistical associations of being close to workers in *other* occupations are confined to the regional level (where effects of same-occupation workers remain positive). We wish to caution here that the results are driven by variance derived from only three regions.

When compare these results to the OLS model in column (5) as well as Table A2 we conclude that there is a good deal of selection in the results without fixed effects. Across the board all OLS coefficients are higher. We take this as an indication that estimating effects of agglomeration economies without accounting for sorting will lead to bloated coefficients (Combes et al. 2008). Nevertheless, the OLS-results clearly show that wages of workers who work in clusters dense in own-occupation workers are substantially higher.

Turning to the control variables we see that there are no clear patterns concerning the estimated influence of the share of workers with a long university education ($\geq$ 3 years), net of controlling for the worker’s own education and our full range of density variables. The coefficient ranges from slightly positive when estimated without district-level variables, to slightly negative in the presence of district-level variables. All FE coefficients are of modest economic importance, probably owing to the slow-moving nature of this ratio. When estimated in levels without district-level variables (see appendix A2) the coefficient is substantially higher, consistent with an interpretation that any effects of this variable do not materialize immediately. Note that 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 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.

Table 2 turns to the industry- and occupation-disaggregated results. Columns (1)-(3) report results for workers employed in manufacturing, low-end services and high-end services respectively. Columns (4)-(5) show the respective results for occupations characterized by low (< 50 %) and high ($\geq$ 50 %) 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 sub-groups in all specifications. Doubling the number of workers with similar occupations is associated with an increase in the wage income of local workers of 0.2-0.6%, with the higher point estimates coming from workers in nonroutine professions, and the lower bound represented by manufacturing. While the estimated parameter is positive in all sub-groups, there is a tendency for the estimated elasticity to be higher in services compared to manufacturing.

The coefficient associated with density of other-occupation workers in first-order neighbors is positive and statistically significant at the 1% level in advanced services industries and in occupations that rely heavily on non-routine work tasks. These results resonate with the idea that services and non-routine occupations may draw on local diversity and exploit cross-fertilizations between different types of economic activities (Duranton and Puga 2001, Feldman and Audretsch 1999). While the magnitudes of the results are modest compared to the estimated same-occupation coefficients, we also observe positive coefficients in neighboring districts for these sub-groups. A tentative interpretation is that the value of diversity in agglomeration economies may be less distance sensitive than specialization. Overall, the results are in line with an interpretation where knowledge-intensive work tasks are productively performed in dense within-region clusters, supported by surrounding districts rich in diversity as well as a generally dense region with knowledge emanating from many different sources and domains.

Table 2. The influence of density of workers with the same and other occupations on the wage income of workers – panel FE estimates for workers INSIDE metropolitan regions.

	(1) Manufacturing	(2) Low-end services	(3) High-end services	(4) Routine	(5) Non-routine
Density of workers with the same 2-digit occupation, ln)	0.002**	0.005**	0.005**	0.004**	0.005**
	(0.000)	(0.000)	(0.001)	(0.000)	(0.000)
Neighbors, density of workers with the same 2-digit occupation, ln	0.000*	0.000	0.000	0.000	0.000**
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Region, density of workers with same 2-digit occupation, ln	0.041**	0.009**	0.009	0.017**	0.025**
	(0.003)	(0.003)	(0.005)	(0.003)	(0.003)
Density of workers with other occupations, ln	0.002	0.001*	0.004**	0.001	0.003**
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
Neighbors, density of workers with other occupations, ln	0.002**	0.000	0.003**	-0.002**	0.001**
	(0.001)	(0.000)	(0.001)	(0.000)	(0.000)
Region, density of workers with other occupations, ln	-0.035**	0.033**	0.018**	0.012*	0.004
	(0.008)	(0.004)	(0.007)	(0.005)	(0.004)
Share university educated (district)	0.006	-0.026**	-0.003	-0.030**	-0.024**
	(0.009)	(0.004)	(0.008)	(0.005)	(0.004)
Share university educated (1st order neighbors)	0.011	-0.013*	-0.011	-0.000	-0.018**
	(0.007)	(0.006)	(0.008)	(0.006)	(0.005)
Age	0.099	0.020	0.161**	0.032	0.125**
	(0.080)	(0.019)	(0.034)	(0.020)	(0.011)
Age squared	-0.000**	-0.000**	-0.001**	-0.000**	-0.001**
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
University education	0.222**	0.222**	0.328**	0.147**	0.266**
	(0.010)	(0.003)	(0.007)	(0.004)	(0.005)
Employer size (log)	0.008**	0.010**	0.009**	0.010**	0.006**
	(0.001)	(0.000)	(0.001)	(0.000)	(0.000)
Capital (ln)	0.003**	0.004**	0.006**	0.004**	0.006**
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Mover	-0.004**	-0.021**	-0.010**	-0.033**	-0.006**
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
Year FE	YES	YES	YES	YES	YES
SSYK FE	YES	YES	YES	YES	YES
SNI FE	YES	YES	YES	YES	YES
YEARxSNI FE	YES	YES	YES	YES	YES
# of observations	2,086,681	6,952,766	2,268,011	5,356,078	5,972,805
# of workers	401,144	1,516,815	581,909	1,230,982	1,109,323
R-squared	0.112	0.104	0.121	0.075	0.130

Note: The table reports results from an estimation of the model in equation (1) for five different sub-groups of workers. Models (1)-(3) present results for workers based on the industry affiliation of the establishment at which they are employed. Models (4) and (5) presents 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 less 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. All parameters are estimated with a panel estimator with worker-level fixed effects. The underlying data are employees in districts (1 km squares) with at least 100 employees within any of Sweden's main metropolitan regions, i.e. Stockholm, Göteborg or Malmö local labor market regions. Robust standard errors reported within brackets. *** p<0.01, ** p<0.05, * p<0.1.

4.2 Outside metropolitan regions

Our focus on metropolitan regions stems from the argument that skill-bias in agglomeration economies primarily pertain to larger urban areas and cities. However, 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, Göteborg and Malmö). First, empirical analyses of the relative effect of industry specialization diversity on productivity and employment growth finds that there are differences between high- and low-density regions in that specialization appears to matter more in less densely populated as well as less developed cities/regions (de Groot et al 2016, Marrocu, Paci and Usai 2013). Second, recent contributions have argued that empirical research is too focused on large urban areas and that policy prescriptions typically focus on ways of making 'large cities bigger' (Rodriguez-Pose and Storper 2020).

Table 3 replicates the industry- and occupation-disaggregated results for workers in districts outside the main metropolitan regions. By comparing these results to those obtained for metropolitan regions (Table 2), we can give an indication as to whether any influence from our district-level variables are concentrated to metropolitan regions, or whether our results support that these effects may be present in smaller regions as well.

Two things stand out in table 3. First, the district-level same-occupation coefficients remain positive, albeit with slightly lower point estimates on average (while their standard-deviations are also lower, see Table A1). Second, and perhaps most notably, outside metropolitan regions we fail to find evidence pointing to benefits of being close to other-occupation workers, irrespective of spatial level. Indeed, the estimated coefficient is often negative. However, the estimated benefits of same-occupation density remain, at the district level as well as at the level of regions. 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 (c.f. de Groot et al 2016). Our results show that this tendency also applies in the context of the influence agglomeration variables on wages of workers and when 'specialization' is measured in terms of occupations rather than industry.

Table 3. The influence of density of workers with the same and other occupations on the wage income of workers – panel FE estimates for workers OUTSIDE metropolitan regions.

	(1) Manufacturing	(2) Low-end services	(3) High-end services	(4) Routine	(5) Non-routine
Density of workers with the same 2-digit occupation, ln)	0.002**	0.002**	0.002*	0.003**	0.003**
	(0.000)	(0.000)	(0.001)	(0.000)	(0.000)
Neighbors, density of workers with the same 2-digit occupation, ln	0.000	0.000*	-0.000	0.000	0.000
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Region, density of workers with same 2-digit occupation, ln	0.010**	0.005**	0.012**	0.004**	0.007**
	(0.001)	(0.002)	(0.003)	(0.001)	(0.002)
Density of workers with other occupations, ln	-0.003**	-0.004**	-0.004**	-0.004**	-0.004**
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
Neighbors, density of workers with other occupations, ln	-0.001	-0.001	0.000	-0.004**	-0.000
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
Region, density of workers with other occupations, ln	-0.002	-0.002	-0.014**	-0.001	-0.003
	(0.002)	(0.002)	(0.004)	(0.001)	(0.002)
Share university educated (district)	0.047**	-0.031**	-0.024*	-0.039**	-0.009
	(0.008)	(0.006)	(0.011)	(0.005)	(0.006)
Share university educated (1st order neighbors)	0.008	-0.006	-0.032*	0.002	-0.005
	(0.008)	(0.007)	(0.016)	(0.006)	(0.007)
Age	0.029*	0.026	0.038**	0.047*	-0.167**
	(0.011)	(0.038)	(0.002)	(0.019)	(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	0.286**	0.207**	0.265**	0.130**	0.262**
	(0.011)	(0.006)	(0.013)	(0.006)	(0.008)
Employer size (log)	0.021**	0.012**	0.018**	0.019**	0.009**
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
Capital (ln)	0.002**	0.004**	0.003**	0.004**	0.004**
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Mover	-0.024**	-0.033**	-0.011**	-0.044**	-0.007**
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
Year FE	YES	YES	YES	YES	YES
SSYK FE	YES	YES	YES	YES	YES
SNI FE	YES	YES	YES	YES	YES
YEARxSNI FE	YES	YES	YES	YES	YES
# of observations	2,794,717	4,614,515	1,009,431	5,423,155	3,078,582
# of workers	524,382	1,036,616	286,341	1,143,404	641,684
R-squared	0.113	0.104	0.100	0.088	0.140

Note: The table reports results from an estimation of the model in equation (1) for five different sub-groups of workers. Models (1)-(3) present results for workers based on the industry affiliation of the establishment at which they are employed. Models (4) and (5) presents 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 less 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. All parameters are estimated with a panel estimator with worker-level fixed effects. The underlying data are employees in districts (1 km squares) with at least 100 employees outside any of Sweden's main metropolitan regions, i.e. Stockholm, Göteborg or Malmö local labor market regions. Robust standard errors reported within brackets. *** p<0.01, ** p<0.05, * p<0.1.

5. CONCLUSION

In this paper we analyze agglomeration gains in novel ways by using geo-coded longitudinal matched employer-employee data for Sweden. We empirically assess the influence of local density on wages of workers and how the relationship depends on skill similarity as evidenced by occupational domains. We exploit geocoded data and a 1x1 km grid cell and analyze these issues in a model with spatial lags.

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. At the sub-city district level, this effect is only present for workers in advanced services industries and workers having occupations with high fractions of non-routine work tasks, which is consistent with the prediction that such workers are more dependent on cross-fertilization across knowledge and industry domains. The latter interpretation is further supported by the fact that we do not find any of these effects to be present outside of the metropolitan areas.

Taken together, our results are consistent with strong local agglomeration gains for workers who perform interaction-intensive and non-routine type work tasks employed in sub-city districts with many similar workers. Our empirical context thus favors 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 located in an overall dense and diversified city environment, up to and including the level of the full region.

Policy-wise the results of this paper link up to recent arguments that local governments have strong power to control agglomeration effects, as they seem to operate within the confines of cities (cf. Rosenthal and Strange 2019). Because of significant agglomeration effects that operate at small spatial scales, land-use planning policies within cities have potentially large influence economic performance as they set the conditions for the sub-city organization of land and office space (Osman 2019, Pan et al 2020). They therefore influence the location pattern of firms within cities and thus 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 of 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 however provide one motivation for city planners to facilitate selforganized clusters at the sub-city level by allowing for density of e.g. office-space and facilitating access to such clusters for workers throughout a city, e.g. by investments in transportation networks.

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APPENDIX

Table A1. Descriptives for variables in the empirical analyses.

	Metropolitan regions (Stockholm, Gothenburg and Malmö)			Non-metropolitan regions (rest of Sweden)		
	Mean	*Std. deviation (between)*	*Std. deviation (within)*	*Mean*	*Std. deviation (between)*	*Std. deviation (within)*
Wage income (SEK, dependent variable)	332,000	256,300	121,100	282,800	151,500	68,640
District, density of workers with the same 2-digit occupation	690.4	1,728	963	126.5	216.9	110
Neighbors, density of workers with the same 2-digit occupation	256.4	897.3	742	43.71	130.4	109
Region, density of workers with the same 2-digit occupation, ln	10.40	0.857	0.35	7.541	1.081	0.40
District, density of workers with the other occupations	5,798	10,135	5,445	1,365	1,698	776
Neighbors, density of workers with other occupations	26,101	34,117	16,314	5,123	4,993	2,017
Region, density of workers with other occupations, ln	13.24	0.466	0.10	10.39	0.908	0.22
Share university educated (district)	0.271	0.135	0.06	0.165	0.114	0.05
Share university educated (1st order neighbors)	0.281	0.109	0.06	0.200	0.0920	0.05
Age	40.17	11.61	2.79	41.25	12.09	2.73
University education at least 3 years (1=yes, 0=no)	0.230	0.421	0.08	0.108	0.310	0.06
Employer size (total employment in establishment)	430.2	1,387	529	215.0	539.4	164
Capital (book value of physical assets, ln)	9.779	3.993	1.88	10.04	3.654	1.58
Mover	0.182	0.386	0.32	0.129	0.335	0.28

Note: The table reports descriptive statistics for workers that are employed in districts with at least 100 employees in Metropolitan regions (i.e. Stockholm, Malmö or Göteborg local labor market region) and non-metropolitan regions (rest of Sweden), respectively.

Table A2. OLS estimates of the influence of density of workers with the same and other occupations on the wage income of workers, INSIDE metropolitan regions

	(1) OLS	(2) OLS	(3) OLS	(4) OLS
District, density of workers with the same 2-digit occupation, ln)	0.017**	0.017**		
	(0.000)	(0.000)		
Neighbors, density of workers with the same 2-digit occupation, ln	0.000**		0.001**	
	(0.000)		(0.000)	
Region, density of workers with same 2-digit occupation, ln	0.022**			0.047**
	(0.001)			(0.001)
District, density of workers with other occupations, ln	0.002**	0.003**		
	(0.000)	(0.000)		
Neighbors, density of workers with other occupations, ln	-0.000		0.007**	
	(0.000)		(0.000)	
Region, density of workers with other occupations, ln	0.014**			-0.009**
	(0.001)			(0.001)
Share university educated (district)	0.001	0.004*	0.060**	0.063**
	(0.002)	(0.002)	(0.002)	(0.002)
Share university educated (1st order neighbors)	-0.023**	-0.016**	-0.019**	0.034**
	(0.002)	(0.002)	(0.002)	(0.002)
Age	0.053**	0.053**	0.053**	0.053**
	(0.000)	(0.000)	(0.000)	(0.000)
Age squared	-0.001**	-0.001**	-0.001**	-0.001**
	(0.000)	(0.000)	(0.000)	(0.000)
University education	0.074**	0.074**	0.075**	0.076**
	(0.001)	(0.001)	(0.001)	(0.001)
Employer size (log)	0.014**	0.014**	0.017**	0.015**
	(0.000)	(0.000)	(0.000)	(0.000)
Capital (ln)	0.053**	0.012**	0.012**	0.012**
	(0.000)	(0.000)	(0.000)	(0.000)
Mover	-0.064**	-0.063**	-0.063**	-0.064**
	(0.000)	(0.000)	(0.000)	(0.000)
Year FE	YES	YES	YES	YES
SSYK FE	YES	YES	YES	YES
SNI FE	YES	YES	YES	YES
YEARxSNI FE	YES	YES	YES	YES
# of observations	11,328,883	11,328,883	11,328,883	11,328,883
# of workers	2,039,379	2,039,379	2,039,379	2,039,379
R-squared	0.346	0.345	0.344	0.344

Note: The table reports results from an estimation of the model in equation (1) for with different specifications. Model 1 includes all variables. Model 2 only includes the district level, model 3 only the neighborhood level and model 4 only the region level as regards our variables of main interest. All models are estimated using OLS. The underlying data are employees in districts (1 km squares) with at least 100 employees within any of Sweden's main metropolitan regions, i.e. Stockholm, Gothenburg or Malmö local labor market regions. Robust standard errors reported within brackets. *** p<0.01, ** p<0.05, * p<0.1.