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Regional diversification and labour market upgrading: Local access to skill-related high-income jobs helps workers escaping low-wage employment

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ABSTRACT
This paper investigates how the evolution of local labour market structure enables or constrains workers as regards escaping low-wage jobs. Drawing on the network-based approach of evolutionary economic geography, we employ a detailed individual-level panel dataset to construct skill-relatedness networks for 72 functional labour market regions in Sweden. Subsequent fixed-effect panel regressions indicate that increasing density of skill-related high-income jobs within a region is conducive to low-wage workers moving to better-paid jobs, hence facilitating labour market upgrading through diversification. While metropolitan regions offer a premium for this relationship, it also holds for smaller regions, and across various worker characteristics.

JEL codes: J21, J31, R11, R23
Keywords: skill-relatedness network; local labour market; low-wage workers; diversification and structural change; relatedness density

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Regionális diverzifikáció és munkaerő-piaci feljebb lépés: A szakértelemhez kapcsolódó, magas jövedelmű munkahelyekhez való helyi hozzáférés segít az alacsony bérű foglalkoztatásból történő elmozdulásban

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ÖSSZEFOGLALÓ

Ez a tanulmány azt vizsgálja, hogy a helyi munkaerőpiac szerkezetének alakulása hogyan teszi lehetővé vagy korlátozza a munkavállalókat az alacsony bérű munkahelyek elhagyásában. Az evolúciós gazdaságföldrajz hálózatalapú megközelítésére támaszkodva részletes, egyéni szintű paneladatállományt használunk, hogy Svédország 72 funkcionális munkaerő-piaci régiójának szakértelmi közelségi hálózatát megkonstruáljuk. Az erre építő fix-hatás panelregressziók azt mutatják, hogy a képzettséghez kapcsolódó, magas jövedelmű munkahelyek növekvő sűrűsége egy régión belül elősegíti, hogy az alacsony bérű munkavállalók jobb fizetésű munkahelyekre válthassanak, és ezáltal megkönnyíti a munkaerőpiac diverzifikáción keresztüli feljebb lépését. Míg a nagyvárosi térségekben ez a kapcsolat jelentősebb, a kisebb régiókban és a különböző munkavállalói jellemzők tekintetében is érvényes.

JEL: J21, J31, R11, R23

Kulcsszavak: szakértelmi közelségi hálózat; helyi munkaerőpiac; alacsony bérű munkaerő; diverzifikáció és szerkezetváltozás; kapcsolati sűrűség

Regional diversification and labour market upgrading: Local access to skill-related high-income jobs helps workers escaping low-wage employment

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Abstract: This paper investigates how the evolution of local labour market structure enables or constrains workers as regards escaping low-wage jobs. Drawing on the network-based approach of evolutionary economic geography, we employ a detailed individual-level panel dataset to construct skill-relatedness networks for 72 functional labour market regions in Sweden. Subsequent fixed-effect panel regressions indicate that increasing density of skill-related high-income jobs within a region is conducive to low-wage workers moving to better-paid jobs, hence facilitating labour market upgrading through diversification. While metropolitan regions offer a premium for this relationship, it also holds for smaller regions, and across various worker characteristics.

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Introduction

Over a 20-year period, about 30% of local industries are replaced by new ones (*Neffke et al., 2018*), which is accompanied by even more drastic compositional changes in employment between sectors (*Metcalfe et al., 2006*) and occupations (*Hane-Weijman et al., 2022*). In many advanced economies, structural change during the past few decades has brought about diminishing work opportunities in the middle of the wage distribution due to automation and offshoring of routine tasks (*Goos et al., 2014; Gregory et al., 2022*). The growing share of low-wage jobs, often with deteriorating working conditions, highlights the typical concern that these jobs offer limited career opportunities and might constitute a dead-end for the workers involved (*Autor et al., 2006; Goos et al., 2009; Clark and Kanellopoulous, 2013*). This makes it imperative to understand the individual and contextual factors underlying upward wage mobility. However, while numerous studies have explored the role of individual characteristics of low-wage workers in as well as the benefits of public policies for upward wage mobility (*e.g., Andersson et al., 2005; Lucifora et al., 2005; Capellari and Jenkins, 2008; Pavlopoulos et al., 2012*), studies on regional contextual factors facilitating upward wage mobility and escaping low-wage jobs are scarce.

This relative regional ignorance may bias our understanding of the prospects of escaping low-wage work. Because industries and occupations are unevenly distributed in space, country-level polarization in the wage distribution will necessarily play out differently on the underlying local labour markets, as exemplified for Sweden by *Henning and Eriksson (2021*). Additionally, growth and decline of local economic activities are biased by what types of activities are already being carried out in a region, a tenet central to an evolutionary perspective on regional structural change (*e.g., Neffke et al., 2011; Kogler et al., 2017*). What follows is that industrial and occupational dynamics may create more opportunities for workers to escape low-wage jobs in some regions than in others. However, there is a substantial lack of evidence on the connection between the economic diversification of regions and intra-regional inequalities, in general (*Boschma, 2017; Boschma et al., 2023*), and opportunity creation for low-wage workers, in particular.

The aim of the present paper is therefore to assess how the changing composition of jobs (combinations of industry and occupation) in regional labour markets enables or constrains the possibility for workers to escape low-wage jobs. This is done by taking an evolutionary perspective on economic diversification in regions, whereby worker skills and experience are more readily transferable between related jobs. Relying on a detailed individual-level panel dataset provided by Statistics Sweden, we construct skill-relatedness networks for 72 functional labour market regions in Sweden, based on above-expected labour flows between jobs at the national level during the period 2002-2005. We then deploy fixed-effect panel regressions to estimate the likelihood of low-wage workers transitioning into high-income jobs throughout 2005-2012, depending on the local concentration of high-income jobs that are related to their current low-wage job. In this way, we both control for time-invariant unobserved heterogeneity of workers and capture the dynamism of the regional job structure over time.

By taking this approach, we contribute to the literature on regional industrial dynamics, in general, and that on evolutionary economic geography (EEG), in particular. A central challenge for EEG currently is to explore how well-documented patterns of (related) regional diversification improve individual economic opportunities, and for whom (*Boschma et al., 2023*). Additionally, the worker- or firm-level sources and implications of regional diversification have been underexplored in this body of literature (*Boschma, 2017; MacKinnon, 2017; Hane-Weijman et al., 2022*). Our paper contributes to this field of research by connecting low-wage workers to changes in the number of locally available and skill-related high-income jobs. We hypothesize that growing density of such jobs in a region may potentially facilitate the upward wage mobility of low-wage workers by opening new labour market channels between low- and higher-paid jobs. Additionally, we contribute to the literature on low-wage work by addressing calls to combine occupation and industry data to reveal the opportunities for workers in different local labour markets (*Farkas and England, 1988; Avent-Holt et al., 2020)*. This is crucial because the same occupation may be paid differently depending on the industrial context. Our approach also adds information on relatedness to the assessment of job opportunities at the regional level, which enriches existing accounts of analysis on labour market structure in the low-wage literature (*e.g.,* *Vacas-Soriano, 2018; Dwyer and Wright, 2019*). These seemingly parallel literatures are seldom combined, even though one of the most straightforward signs of a successful structural change is the possibility for the workforce to move from low- to high-productivity activities (*Pasinetti, 1981)*.

Our results indicate that, as the density of skill-related high-income jobs within a region increases over time, the higher the likelihood of low-wage workers moving to better-paid jobs. While metropolitan and/or growing regions offer a premium for this relationship, it also holds for smaller regions, as well as across various worker characteristics. Thus, in regions where branching increases skill-related high-income connections, even workers in low-wage jobs have a greater chance of finding new jobs with a higher income level.

The next section provides the conceptual motivation for the study, the third presents the data and methods followed by the results in the fourth section. The fifth section concludes the paper.

Regional diversification and escaping low-wage jobs

The labour market polarization literature has drawn attention to how recent patterns of technological change and globalization have led to polarization through the changing composition of jobs by adding new employment in low- and high-wage occupations while hollowing out the middle (*Autor et al., 2006; Goos and Manning, 2007; Goos et al., 2009*). For instance, *Acemoglu and Restrepo (2022)* reported that between 50% and 70% of changes in the wage structure in the US over the past 40 years can be attributed to relative wage declines for worker groups specialized in routine tasks that were under considerable pressure from automation and offshoring. Similar conclusions can be draw for European economies (*Gregory et al., 2022*), and in fact low-wage employment has become a common and persistent feature of European labour markets (*Lucifora et al., 2005; Nickel et al., 2019*).

The growing share of low-wage jobs, often coupled with deteriorating working conditions (*Dwyer and Wright, 2019; Kalleberg, 2020; Krings, 2021*), is concerning, because such jobs may offer limited career opportunities and may constitute a dead-end for the workers involved, especially due to their persistence across an individual’s working life (*Bills et al., 2017*). Due to the spatial division of labour, economic activities, in particular jobs, are unevenly distributed across space (*Wixe and Andersson, 2017*). This implies that national patterns of income polarization due to structural change unfold unevenly across local labour markets. For instance, evidence from Sweden indicates that the income polarization observed at the national level is driven by polarization and spatial sorting in Stockholm, Sweden's largest metropolitan area, and by manufacturing regions with a low-skilled workforce, while other regions still follow the traditional labour market upgrading model (*Henning and Eriksson, 2021*). What follows is that regional economies show a heterogeneous capacity for positive change or for confining workers in a low-wage trap with limited scope for upgrading (*Green et al., 2020*).

But how does the composition of jobs in the local labour market bring about opportunities to escape low-wage jobs? Research on industrial dynamics has consistently documented the interdependence of sectorial rates of firm entry and exit (*e.g., Disney et al., 2003; Manjón-Antolín, 2010*). As industries decline, from a resource-based perspective (*Neffke et al., 2018*), previously used resources including labour are freed up to be potentially redeployed in new industries. The most straightforward mechanism for employment reallocation is the local job changes of workers with skills and experiences that can be applied in other industries (*Morkuté et al., 2017*). Hence, these employment reallocations form dynamic pools of labour between multiple sets of industries, as well as between growing and declining ones (*Morkuté et al., 2017; O'Clery and Kinsella, 2022*). The EEG literature has also shown that new economic activities in regions do not emerge at random, but in many cases branch out of activities that are already present (*Frenken and Boschma, 2007; Neffke et al., 2011*, for overviews see *Content and Frenken 2016; Hidalgo 2021*). Besides local reallocation, workers may respond to shifts in local economic structures or seek out better-paid jobs by moving to other regions for work, although switching between industries is generally more common than moving (*Neffke and Henning, 2013*). Finally, escaping low-wage jobs may be possible through a firm-internal career, whereby gradual skill accumulation allows workers to switch to better-paid jobs.

The common element in each of these alternatives is that the existing set of worker skills limits the possibilities for reallocation within the firm, across economic activities within the local economy, or across regions. Previous research has shown that the time to re-employment after displacement in relation to plant closures is significantly shorter in regions with more skill-related jobs (*Hane-Weijman et al., 2018*), and that displaced workers are more inclined to find new employment in sectors that are similar or related to their previous sector of work (*Eriksson et al., 2018*). This labour market channel is also typically associated with better income development compared to mobility to more unrelated activities (*Eriksson et al., 2016*), something that, according to *Holm et al. (2016),* signals a creative destruction in which more productive (and higher-paying) regional activities are reinforced and less productive (and lower-paying) activities decline. Findings at the regional scale suggest that increasing intensity of skill-related moves enhances regional growth, which, according to *Boschma et al. (2014*), indicates the prospects for inter-industry pooling and matching externalities.

The open question is then whether structural change unfolding over a spatially heterogeneous polarization of income and activities bridges the gap between low- and high-wage jobs, hence creating or foreclosing opportunities for escaping low-wage jobs. In the present paper, we engage with this question by taking an evolutionary perspective on structural change and building on the central tenet of the EEG literature on related regional diversification. As it remains unclear how industrial dynamics is related to intra-regional inequalities (*Pinheiro et al., 2022; Boschma et al., 2023*), we propose that, moving forward, it is a crucial challenge for the EEG literature to investigate in depth whether and how regional branching creates more or less economic opportunities, and for whom.

To be sure, it is not straightforward whether regional diversification reinforces polarization and wage inequalities within regions. Due to formal barriers like education, as well as heterogeneous returns to skills (*Czaller and Hermann, 2023*), better paid jobs may be more related to other better paid jobs. Additionally, individual workers tend to diversify into skills related to their existing set of skills, which, together with the polarization of socio-cognitive and sensory-physical skills, was found to create a bottleneck for US workers in reaching occupations with a higher share of socio-cognitive skills and wage returns to skills (*Alabdulkareem et al., 2018*). In the case of a strongly segmented labour market, related diversification would actually contribute to polarization and income inequalities by reinforcing the local labour market structure in both the low- and high-end segment, respectively. At the extreme, plants that are first in their region within a specific industry tend to source labour initially from outside the region for high-skilled positions, while sourcing employees for low-wage work locally (*Hausmann and Neffke, 2019*). Additionally, if exiting jobs are more unrelated to the regional portfolio, as is on average the case (*Neffke et al.,* *2011*), this will limit local reemployment possibilities for workers (*MacKinnon, 2017*) or force reemployment under worse matching conditions.

On the other hand, related diversification could also create new opportunities for gradual upgrading of the local labour market if new high-paid jobs are related to the low-wage jobs. This could open a channel for career advancement without formal barriers, as intermediate job opportunities would be developed in regions and could serve as bridges between low- and better-paid jobs. This would create an upgrading challenge akin to that of transitioning from low- to high-complexity economic activities, whereby reaching an intermediate level of economic complexity proves the most difficult, due to predominantly related diversification into low-complexity activities early on (*Pinheiro et al., 2021*). There is recent evidence indicating that particularly the entry of related low-complexity industries decreased wage inequalities in Dutch regions, while the exit of unrelated ones increased them (*Cortinovis et al., 2022*). It remains unclear, however, whether and through what intermediary steps low- and high-wage jobs form pools of skill-related labour.

Additionally, since polarization is more pronounced in some regions than in others (*Henning and Eriksson, 2021*), the interplay between regional branching and a polarized labour market likely has spatial heterogeneity. Higher value-added and more complex economic activities concentrate in large cities (*Kemeny and Storper, 2020; Balland et al., 2020*), and high-income regions have a higher frequency of entering and potential to enter high-complexity activities (*Pinheiro et al., 2022*). While this potentially reinforces existing income structures at the higher end, high-tech jobs tend to generate employment for low-skilled workers through local multipliers, but mostly in poorly paid service work (*Florida, 2017; Lee and Clarke, 2019*). Hence, in large cities in particular, related diversification may reinforce polarization not only directly, but also through local multipliers. Further, regions with specializations in low-skilled manufacturing also show a polarized wage structure (*Henning and Eriksson, 2021*), and skilled jobs in manufacturing tend to have relatively higher local multipliers due to higher earnings (*Moretti, 2010*).

Based on the above, we expect that gradual change in the regional job structure creates opportunities or barriers for upgrading depending on the degree of transferability of skills between the low- and high-paid labour market segments. Opportunities for workers to escape low-wage jobs would be possible particularly when there is an increase in better-paid jobs in the local labour market that are also skill-related to their existing low-wage job. In such regional environments, we expect structural change to be smoothened, as it would both reinforce high-income activities and provide a career channel for local workers in low-wage jobs, thus potentially reducing intra-regional polarization and enabling a more inclusive regional development. In the remainder of the paper, we test this expectation in the context of Swedish labour market regions.

Data and methods

Data description

For the analysis, we rely on individual-level panel data from Statistics Sweden covering the period 2002-2012, which includes information on annual wages and other characteristics of individuals active on the Swedish labour market, as well as their occupations and industry affiliations. 2002-2012 was chosen for one main reason: consistent and reliable information on occupations is available only for this period.

To define a *job*, we follow the methodology of *Henning and Eriksson (2021)* by combining the occupation code with the industry code. This is because the task content of a specific occupation may be different across industries (see *Goos and Manning, 2007*). For occupations, we use the 3-digit level of the Swedish SSYK96 occupation nomenclature (consistent with the international ISCO-88); for industries, we use the 2-digit level of the SNI2007 industry classification system (consistent with NACE Rev. 2.). Jobs with fewer than 100 employees were excluded to account for spurious combinations, resulting in a final set of 1791 jobs, representing about 95% of the total workforce.

For each of these jobs, we calculate the median wage in 2005. To increase the reliability of these values, the following steps were taken. First, individuals who are not registered as "employed" or who have changed workplace during the previous two years (people who change jobs tend to receive higher incomes) were excluded. Second, the remaining sample within each job was sorted into wage deciles and the first and tenth deciles were removed, to exclude potential outliers. As reported by *Henning and Eriksson (2021)*, excluding only the top and bottom 5%, or using the entire sample, does not influence the general pattern of job classification. Finally, based on the distribution of median wage across jobs in 2005, we assign the jobs into quintiles.

This classification approach is based on the strategy proposed by *Goos et al. (2009)* and replicates the classification strategies established by *Fernández-Macías (2012)* and *Henning and Eriksson (2021)*. That is, in the present paper, we rely on a job-based definition of *low-wage jobs*, where we consider the bottom three quintiles based on the median wage distribution of jobs to be low-wage. Note that this implies that workers will not be evenly distributed across the job quintiles.

Hence, our sample of analysis consists of all workers aged 18-64 registered as having their main income from employment and belonging to the lowest three job categories. Because annual earnings may be a biased measure of wages for individuals working part-time, we are forced to exclude observations that are registered as having study loans or stipends from education registers, income from parental leave or unemployment. After excluding observations with missing data, or longer spells of inactivity, low-wage workers constitute about 30% of the total sample of workers (see *Table A1* in Appendix).

As shown in *Table A1*, the low-wage sample is fairly evenly distributed across different types of regions, but it is somewhat more likely that a metropolitan low-wage worker moves to a higher-wage category (53%). These workers earn on average about 84 thousand SEK (1 Euro is about 10 SEK) less than the total workforce on an annual basis. Although there are no great differences in terms of educational levels or age, there is an over-representation of women and individuals born in the Global South. Low-wage workers are more likely to have occupations like service and sales and clerical support as well as general elementary occupations, while in terms of broad sectors, health and social work activities, wholesale and retail, and education are the most common.

Network construction and variable of interest

We capture the feasible transitions between jobs by means of a *skill-relatedness network*. This network rests on the idea that, on average, workers tend to switch between roles where they can carry over their accumulated skills (*Neffke et al., 2017*). This approach of revealed relatedness combines labour flows within and across geographical units, time and labour markets segments, revealing a normalized labour reallocation intensity between pairs of economic activities on average. In this analysis, two jobs are considered skill-related if the observed labour flow between them (F_{ij}) exceeds what we would expect based on the propensity of these jobs to experience labour flows ($(F_{i.}F_{.j})/F_{..}$):

$$SR_{ij} = \frac{F_{ij}}{(F_{i.}F_{.j})/F_{..}} \tag{1}$$

Here, $F_{i.}$ is the total outflow of workers from job i, $F_{.j}$ is the total inflow to job j, and $F_{..}$ is the total flow of workers in the Swedish economy. To arrive at the final measure of skill-relatedness between jobs, we consider the average of SR_{ij} and SR_{ji} to receive a symmetric measure, we normalize[1] the measure to have its range between -1 and +1 and keep only those links that have a normalized skill-relatedness above 0, corresponding to above-expected labour flows. The network is based on labour mobility between 2002-2005[2], and this it does not overlap with the period over which the wage mobility of low-wage workers is assessed.

Next, the national skill-relatedness measure is applied to each region by considering a job to be present in a local labour market if that region shows relative specialization in that job. This is a common way of considering local economic structure in the literature on relatedness (for an overview see *Hidalgo, 2021*). In particular, the location quotient of employment tells us how over- or underrepresented the employment of a job i in a region r in year t is compared with the job's employment share in the national economy of Sweden:

$$LQ_{i,r,t} = \frac{EMP_{i,r,t}/EMP_{r,t}}{EMP_{i,t}/EMP_{t}} \tag{2}$$

A job is considered present in a region if its location quotient is above 1. A region in the analysis refers to one of 72 functional labour market regions.

[1] This is done because the distribution of the skill-relatedness values is strongly right-skewed (*Neffke et al., 2017; Neffke et al,. 2018*). The normalization maps these values between -1 and 1: $\widetilde{SR}_{ij} = \frac{SR_{ij}-1}{SR_{ij}+1}$.

[2] *Neffke et al. (2017)* reported very strong correlation of inter-industry labour flows measured 10 years apart, indicating that it is reasonable to not consider the potential change in skill-relatedness in our analysis. We also tested whether pooling additional years would change the structure of our network, but found that there was a strong edgewise correlation between the extended time pools and the one used in the paper.

The share of skill-related connections that are not only feasible, evidenced by the overall network, but also available for workers of a particular region can be measured by *relatedness density*, an established measure of how related an economic activity is to the regional portfolio (for an overview see *Hidalgo 2021*). Specifically, we consider the relatedness density ($RD_{i,r,t}$) of job i in region r in year t to be:

$$RD_{i,r,t} = \frac{\sum_i SR_{ij} I(LQ_{j,r,t})}{\sum_i SR_{ij}} \tag{3}$$

Here, $I(LQ_{j,r,t})$ is an indicator variable, showing whether region r in year t has relative specialization in job $j \neq i$ (taking the value of 1) or does not (taking the value of 0). In essence, this measure reveals what percent of skill-relatedness to other jobs[3] is available in the region for a worker in a particular job. Consequently, the temporal variation of this measure comes from the gradual change in the specialization structure of a particular local labour market relative the national economy. Note that, by using a dichotomized location quotient in this calculation, we assume that there is a critical mass of an agglomerating related job, above which it is considered in the density measure. While widely used for constructing such a measure (*Hidalgo, 2021*), this approach has also been contested in the literature, and more activity-specific cut-offs for identifying a critical mass of agglomeration (*Cortinovis et al., 2017*), as well as more continuous approaches (*Davies and Maré, 2021)*, have been proposed. Our robustness tests using these alternative approaches are discussed in the *Sensitivity analysis* subsection, while a more detailed discussion is provided in the Appendix.

Finally, the main variable of interest in the empirical analysis is a version of the relatedness density measure that also takes into account whether a particular job can be considered high-income. Specifically, the *high-income relatedness density* ($HI.RD_{i,r,t}$) of job i in region r in year t is:

$$HI.RD_{i,r,t} = \frac{\sum_i SR_{ij} I(LQ_{j,r,t}) I(ICAT_j)}{\sum_i SR_{ij}} \tag{4}$$

[3] Note that the measure not only counts the number of connected jobs, but also considers the strength of these connections. Hence, it is the share of tie weights connecting a job to others present in the region.

Here, the new term $I(ICAT_j)$ indicates whether a job has been classified in the top two quintile bins of the median income distribution detailed above. Hence, this version of relatedness density measures the percent of skill-relatedness connecting a job to locally available jobs that are also high-income.

Figure 1 shows the distribution of relatedness density to high-income jobs within each of the 72 labour market regions that we observe, as well as the network representation of local labour markets through three highly different example cases captured in 2006. We observe, first, that high-income relatedness density has a right-skewed distribution, as many jobs have relatively weak local concentration of related high-income jobs. Second, crucial to our investigation, there is considerable variation in the high-income relatedness density of jobs within each region. Third, moving up the population density ranking, we find more and more richly connected jobs in the network representation of local labour markets, from small (*e.g.*, Åsele), to medium (*e.g.*, Umeå), to metropolitan regions (*e.g.*, Stockholm). *Table A2* of the Appendix provides examples of jobs with high and low relatedness density in these different regional settings.

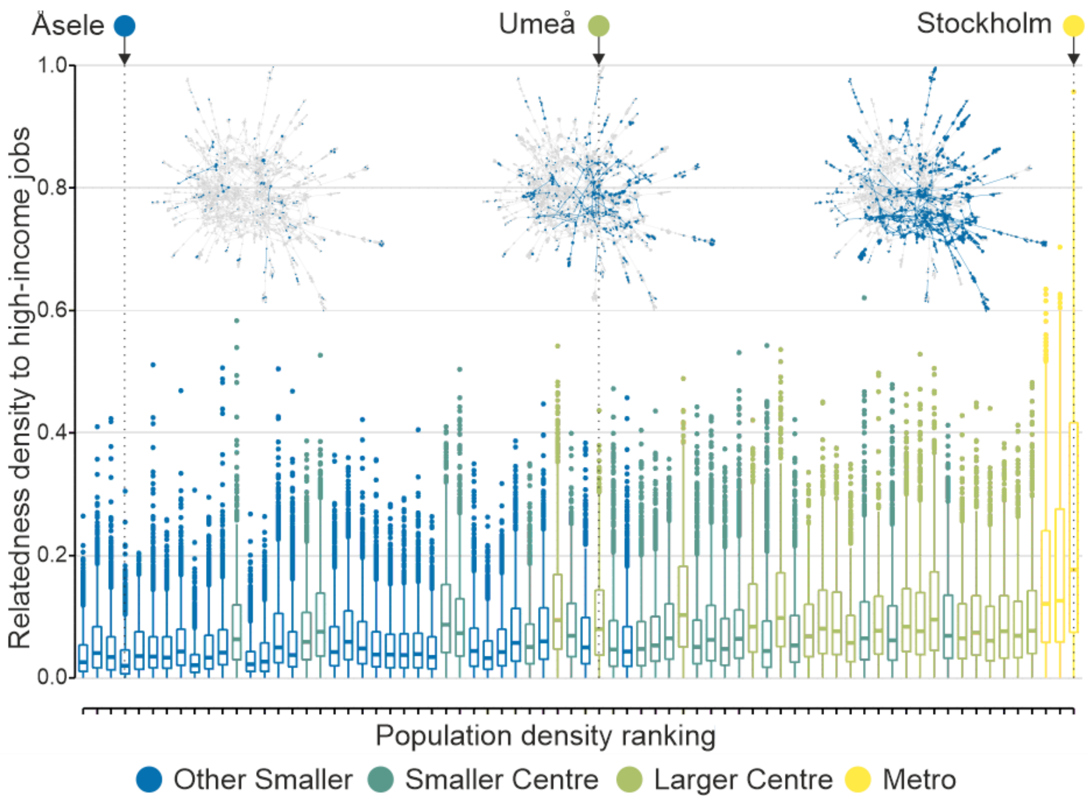

Figure 1. Relatedness density to high-income jobs by region type in 2006.

We find a modest but statistically significant 0.46 Pearson-correlation coefficient between the median incomes of pairs of jobs, showing that the network is median-income assortative (*i.e.,* high-income jobs are more likely to be connected with other high-income jobs). Conversely, 65-94% of connections of the ten most frequent low-wage jobs in our sample are to other low-wage jobs (*Table A3* of the Appendix), and more generally a large (although with variation) share of skill-related connections of low-wage jobs are other low-wage jobs (*Figure A1* of the Appendix).

Econometric model

To estimate the likelihood of transitioning from a low-wage job to a higher-wage job, we exploit the time dimension in our data by comparing the job of a given individual at $t-1$ with t. If the worker has switched to a higher-paying job (*i.e.*, to any job in the two highest income categories from any category of the three lowest-paying categories) within the region, this is coded 1 (and otherwise 0). This approach draws on the low-wage literature, where escaping low-wage is commonly examined by dichotomizing the dependent variable (*e.g., Andersson et al., 2005; Lucifora et al., 2005; Vacas-Soriano, 2018*)[4] to reveal factors that help workers move above such a low-wage threshold.

We focus in the main analysis on within-regional job changes in the analysis, as about 90% of all changes occur within the same local labour market, and we are primarily focusing on how the evolution of regional economies influences upgrading in the existing regional workforce. As noted in *Table A1* (Appendix), however, there is a slight over-representation of inter-regional job changes among the low-wage workers who move upwards (13% compared to 10%). An additional sensitivity analysis of inter-regional job mobility is provided in the *Sensitivity analysis* subsection.

Due to this binary outcome and the panel data at hand, we use a fixed-effect linear probability model when estimating the likelihood of moving upwards, and we present results from a conditional logit model in our sensitivity analyses. Although a logistic (conditional) regression would be the standard approach, linear probability models are more accurate for

[4] A sensitivity analysis using alternative definitions instead of our main, quintile-based, approach is provided in the *Sensitivity analysis* subsection.

panel data like ours when the number of observations is large and the event ($y = 1$) is rare (*Timoneda, 2021*). In our case, about 3% of all low-wage workers make a move to a high-income job (see *Table A1* in Appendix). A fixed-effect panel model allows us to account for the well-known fact that unobserved characteristics of workers may bias the results. Workers with better abilities, more motivation, or with better social connections may have greater possibilities to find new jobs. By stressing the within-variation over time instead of comparing different low-wage workers, we estimate the likelihood of experiencing upward job mobility as the density of the related job changes from year to year:

$$Y_{i,t} = \beta X_{i,t-1} + \gamma C_{i,t-1} + u_i + \tau_t + \varepsilon_{i,t} \tag{5}$$

Here $Y_{i,t}$ is the binary outcome variable for low-wage worker i at time t, $X_{i,t-1}$ is the vector of our main variables of interest at time $t-1$, $C_{i,t-1}$ is the vector of the control variables at time $t-1$, u_i and τ_t are the respective worker- and year-specific fixed-effects and $\varepsilon_{i,t}$ is the error term.

Although the fixed-effect model has some advantages for causal inference, it cannot compute the estimates of the effects of time-invariant variables (*e.g.,* gender or country of birth) because individual changes are absent. Thus, all such observed and unobserved factors that are considered fixed within individuals over time, but still may influence the outcome, are omitted. Consequently, we must restrict our control variables to time-variant information. At the individual level, we control first for the fact that younger segments of the workforce switch jobs more often and tend to be over-represented in low-wage jobs. Apart from that, age (AGE) also proxies general accumulated experience, which may increase the likelihood[5] of escaping low-wage jobs (*Schultz, 2019*). Additionally, we include income from work ($\ln INCOME$) as a controller. This is important, because the low-wage sample is based on the median income in each job, which also means income variation within a given job. Relative high-income earners in a low-wage job could signal a relatively better possibility of further career advancement (see *Andersson et al., 2020*).

5 Age sometimes has a non-linear relationship with career mobility. We therefore originally included the square term of age, but although it was (weakly) significant, it did not influence the general results and is therefore omitted from the final models.

At the regional level, we include two proxies for agglomeration. First, population density ($\ln POPDENS$) controls for the size and general job opportunities of the local job market. Population density is usually strongly related to income development (*Duranton and Puga, 2004*), but it is also often used as a catch-all regional controller (*Boschma et al., 2014*). Then a more detailed controller of the local job market is added by summing the number of workers in each job ($\ln JOBSIZE$). This is done because jobs with a large internal local market usually imply a higher likelihood of finding new employment opportunities within the same labour market segment as well as of building an internal job career as opposed to jobs that are not as frequently represented in the region (*Eriksson et al., 2018*). The share of high-income jobs ($PCT.HINCJOB$) is included to control for the average size of the high-income job market, which could influence the likelihood of upward mobility. Both employment rate ($PCT.WORKAGE$) and average regional workplace size ($AVG.WPSIZE$) are typical controllers for regional development and job mobility, as employment opportunities tend to vary along these dimensions (*Morkuté et al., 2017*). Yearly dummies are used to control for time-specific heterogeneity that may influence all workers in a similar way, like changes in policy or the recession of 2008-2010.

Due to the skewed distribution on income, density and size of regional jobs, these variables are log-transformed. Moreover, to reduce the impact of simultaneity, we use the lags of each right-hand side variable in the regressions. The regression sample is therefore restricted to the years 2006-2012. *Table A5* of the Appendix summarizes the main variables. There are no obvious signs of multicollinearity, the highest pair-wise correlations are between population density, share of high-income jobs, employment rate and job size (ranging between 0.35 and 0.72). Omitting any of these variables did not influence our interpretation of the models.

Results

Descriptive results

We first provide simple descriptive evidence showing that the association between relatedness density and changing to better-paid jobs is economically significant. To do so, we bin the distribution of relatedness density to high-income jobs ($HI.RD$) across time into four quartiles. As one can expect that the local opportunity structure varies depending on the spatial division of labour, we perform this binning separately within four different categories representing the spatial hierarchy of labour market regions in Sweden. Finally, we calculate for each quartile bin the percent of workers with a job in the lowest three wage categories who transition into the top two from one year to the next, pooled across the period 2005-2012 (*Figure 2*).

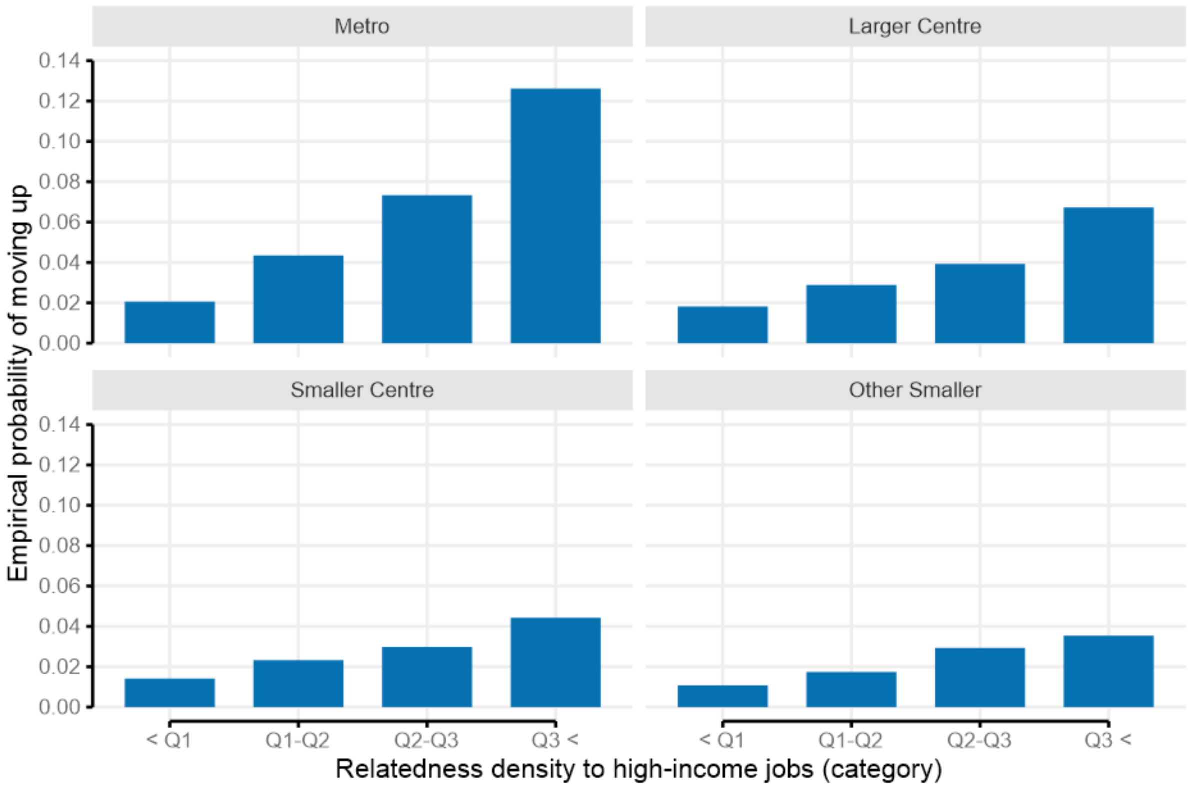

Figure 2. Empirical probability of switching to high-income job by region type.

First, we find that more upward mobility occurs in higher quartiles of relatedness density to high-income jobs in all region types considered. Second, we find that the boost from relatedness density to the propensity to move to better-paid jobs increases more sharply with moving up in the spatial hierarchy. That is, moving from the lowest to highest bin in relatedness density to high-income jobs, the probability of wage mobility increases from 1% to 4% in the smallest labour market regions, while it increases from 2% to 13% in metro regions. This indicates that there is an urban premium in the benefits of relatedness density to high-income jobs, partially due to the already higher network density in metro regions. However, as evidenced previously by *Figure 1*, the unique feature of metro regions is in having higher relatedness density at the upper end of the distribution, while also having plenty of jobs with low relatedness density. Hence, we find in *Figure 2* that all region types have similar probability for wage mobility in the lowest bin of relatedness density (1-2%). This also indicates a polarization in the probabilities of upward mobility in a metropolitan setting, and that the local opportunities for jobs with few other skill-related jobs present are indeed scarce in a thicker labour market as well.

Regression results

While this set of evidence offers important initial insights into the significance of relatedness density for high-income jobs in an economic sense, it amounts to a simple descriptive, and so we now turn to the main regression results (*Table 1*). *Model 1* represents the baseline specification with only the control variables included. Then we test whether change in relatedness density (RD) as such creates opportunities for upward mobility (*Model 2*), followed by our main specification assessing how change in relatedness density to high-income jobs ($HI.RD$) influences upward mobility. *Model 4* to *6* offer robustness checks.

Control variables show expected signs (*Model 1*), and with reasonable exceptions maintain them across specifications. Higher age (AGE) is positively correlated with upward mobility across all specifications (but with weak downward slope if also including the square term). Workers in low-wage jobs experiencing a relatively faster wage development ($INCOME$) are also more likely to switch to better-paid jobs. In terms of the regional variables, an increasing share of high-income jobs in the local job portfolio makes upward mobility more likely ($PCT.HINCJOB$). This is not the case, however, when introducing regional fixed effects in *Model 4*. Increasing population density ($POPDENS$) as well as employment rate ($PCT.WORKAGE$) are both positively associated with upward mobility. This is expected, given the diversity of job opportunities that is generally associated with both expanding labour markets and higher employment rate. Average establishment size ($AVG.WPSIZE$) is negatively associated with upward mobility, likely because less inter-firm competition for workers makes such mobility more challenging. Finally, the size of the particular job in the region ($JOBSIZE$) mitigates job mobility as expected, given the greater likelihood of finding new employment opportunities within the same job in regions with an expanding local job market.

Table 1. Fixed-effect linear probability models on the within-regional career mobility of low-wage workers 2006-2012.

LHS (sample)	**(1)** Into top 2 (all LW)	**(2)** Into top 2 (all LW)	**(3)** Into top 2 (all LW)	**(4)** Into top 2 (all LW)	**(5)** Into top 3 (LW1-2)	**(6)** Income change (all LW)
RD_{t-1}		0.003***				
		(0.001)				
$HI.RD_{t-1}$			0.070***	0.071***	0.121***	0.262***
			(0.003)	(0.003)	(0.005)	(0.004)
AGE_{t-1}	0.007***	0.007***	0.007***	0.005***	0.010***	0.014***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
$\ln INCOME_{t-1}$	0.009***	0.009***	0.009***	0.009***	0.015***	-0.783***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.001)
$PCT.HINCJOB_{t-1}$	0.100***	0.102***	0.098***	0.017	0.222***	0.012
	(0.011)	(0.011)	(0.011)	(0.011)	(0.017)	(0.020)
$\ln POPDENS_{t-1}$	0.005***	0.004***	0.003***	0.190***	0.004***	0.014***
	(0.000)	(0.000)	(0.000)	(0.004)	(0.001)	(0.001)
$PCT.WORKAGE_{t-1}$	0.277***	0.275***	0.261***	0.399***	0.396***	0.495***
	(0.011)	(0.011)	(0.011)	(0.014)	(0.017)	(0.020)
$AVG.WPSIZE_{t-1}$	-0.003***	-0.003***	-0.003***	-0.012***	-0.003***	-0.007***
	(0.000)	(0.000)	(0.000)	(0.001)	(0.001)	(0.001)
$\ln JOBSIZE_{t-1}$	-0.004***	-0.004***	-0.003***	-0.003***	-0.007***	-0.000
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Constant	-0.440***	-0.441***	-0.437***	-1.261***	-0.681***	3.554***
	(0.005)	(0.005)	(0.005)	(0.017)	(0.008)	(0.011)
Worker FE	YES	YES	YES	YES	YES	YES
Year FE	YES	YES	YES	YES	YES	YES
Region FE	NO	NO	NO	YES	NO	NO
N (worker-year)	13,759,534	13,759,534	13,759,534	13,759,534	9,124,751	13,759,534
n (worker)	3,199,126	3,199,126	3,199,126	3,199,126	2,296,099	3,199,126
Within R^2	0.011	0.011	0.012	0.012	0.017	0.432

Notes: standard errors in parentheses; * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Turning to the main variable of interest, our findings suggest that increasing relatedness density as such (RD) is positively associated with upward mobility (*Model 2*), indicating a slight overall upgrading following related diversification. However, an increasing density of higher-paid jobs ($HI.RD$) increases in particular the probability of moving upwards in the wage distribution (*Model 3*). This finding remains robust when also adding region-specific fixed effects (*Model 4*). The relationship between increasing density and career mobility is likely because of the assortativity of the job network, where high-income jobs tend to be connected with other high-income jobs. Hence, upward mobility is boosted particularly by low-wage jobs that are nevertheless better connected to better-paid alternatives. To ease assessment of the economic significance of these findings, we computed the marginal effects of *Model 2* and *3* using standardized versions of the variables. The findings of this test, reported in *Table A5* of the Appendix, indicate that a one standard deviation increase in high-income relatedness density increases the probability of upward mobility by 1 percentage point. This exceeds relatedness density by a factor of ten and is also larger than the percentage point effect of raising income, share of high-income jobs, employment rate or population density by one SD (0.5, 0.2, 0.9 and 0.3 percentage points, respectively). Hence, the role of high-income relatedness density supersedes population density in the probability of escaping low-wage jobs. One standard deviation increase in age, however, has a greater impact, which signals the role of accumulated experience in escaping low-wage jobs (*Schultz, 2019*).

Taken together, the outcomes of *Model 2-4* largely confirm the notion that if regional branching entails diversification into better-paid jobs that are also related to low-wage jobs, then the likelihood of workers in low-wage jobs advancing also increases. This in turn could signal the possibility for a structural change in which existing regional capabilities could be used in new ways to reinforce more highly paid activities, thus simultaneously supporting regional upgrading and career mobility at the micro-level. However, different mechanisms might influence this. To provide more detailed assessments of exactly how high-income relatedness density influences upward job mobility, several further estimations have been performed as sensitivity analyses.

Sensitivity analysis

To test whether our findings are driven by the definition of low-wage jobs, in *Model 5* of *Table 1* the low-wage category was changed to include only the bottom two quintiles and the likelihood of changing jobs into the top three was estimated, yielding an even larger coefficient on the main variable of interest (which still measures relatedness to the top two categories of high-income jobs). This indicates that this channel of upward mobility also works for the workers in the lowest-paid jobs. Moreover, in *Model 6* we tested income change as a continuous dependent variable instead of switching between categories. The result indicates a strong positive association between high-income relatedness density and income growth of workers in low-wage jobs, thus signalling a potential spill-over effect within clusters of skill-related jobs.

Because we know that certain groups, such as immigrants, women and low-educated individuals, are more likely to obtain low-wage jobs and also perhaps lack the necessary resources to escape such employment, we have constructed a number of additional interaction models to assess whether the impact of relatedness density is significantly different across sub-groups of the workforce (not reported). There was no significant interaction of relatedness density and women and immigrants, respectively, whereas increasing relatedness density increased the probability of low-educated workers escaping such employment to a greater degree, signalling that, for workers with less generic human capital, a skill-related career path might be a crucial resource.

Next, we tested whether alternative specifications of the relatedness density measure would change our results. In short, using a job-specific cut-off to identify a critical mass of agglomerating related jobs (*HI.RD.BSTRAP*), following *Cortinovis et al. (2017*), or using the share of a job in the local employment structure as input to calculating relatedness density (*HI.RD.LSHARE*), as proposed by *Davies and Maré (2021*), did not change our findings (*Table 2*). In fact, the latter approach yields somewhat higher estimates when comparing standardized coefficients, indicating that our main models may underestimate the benefit of relatedness density (see additional details on calculating these variables at the end of the Appendix).

Additional robustness checks are reported in *Table A6* of the Appendix. To summarize these, in *Model 7* we focus only on workers earning less than 60% of the national median income from work any given year, thus corresponding to the recurring definition of low-wage workers (*Vacas-Soriano, 2018*). When estimating the likelihood of moving from this traditional low-wage category to the group with incomes above 60% of the median, we also find a strong positive association between relatedness density and the likelihood of escaping low-wage work. It should be noted that, in this case, the upward mobility rate increases from 3% to almost 7%. In *Model 8* and *9*, we differentiate between upward mobility specifically into the fourth or fifth (highest) income category of jobs, finding a similar coefficient compared with our main model, though also finding that high-income relatedness density offers a smaller boost for jumping to the highest income category.

Table 2. Alternative identifications of locally significant jobs (standardized indicators).

LHS (sample)	**(1)** Into top 2 (all LW)	**(2)** Into top 2 (all LW)	**(3)** Into top 2 (all LW)	**(4)** Into top 2 (all LW)
RD_{t-1}	0.000*** (0.000)			
$HI.RD_{t-1}$		0.011*** (0.000)		
$HI.RD.BSTRAP_{t-1}$			0.004*** (0.000)	
$HI.RD.LSHARE_{t-1}$				0.015*** (0.000)
Controls	YES	YES	YES	YES
Worker FE	YES	YES	YES	YES
Year FE	YES	YES	YES	YES
Region FE	NO	NO	NO	NO
N (worker-year)	13,759,534	13,759,534	13,759,534	13,759,534
n (worker)	3,199,126	3,199,126	3,199,126	3,199,126
Within R^2	0.011	0.012	0.012	0.012

Notes: standardized variables; standard errors in parentheses; * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

To test whether co-mobility of workers drives our results, *Model 10* focuses on a subsample in which only one move per workplace was included. This also does not alter our main findings. In *Model 11* and *12*, we isolate cases where occupation and industry, respectively, are held constant. This test goes somewhat against the grain of the job definition employed in the present paper, as we argue that different task bundles of workers are most accurately represented by a combination of industry and occupation codes. Still, we find positive associations between upward mobility and high-income relatedness density, with a somewhat higher coefficient in cases where workers remaining in the same occupation transition into a different industry. Next, to test whether our results are driven by workers making an internal career at firms, in *Model 13* we isolate cases in which the workplace of the workers was changed, once again reinforcing our main finding. In *Model 14*, we show that while relatedness density to high-income jobs is associated with wage increase, there is a premium to this in cases where low-wage workers change workplaces. Taken together, *Model 13* and

14 support the notion that the increasing presence of related jobs creates new perceived opportunities to find new, better-paid jobs in the region. *Model 15* provides results on the main regression in a conditional logit specification, supporting our main findings.

We further tested whether an increase in relatedness density (to high-income jobs) is associated with alternative outcomes besides upward mobility within the region, such as downward mobility from high-income jobs to lower categories or moving to another region for work. Such outcomes could potentially come about if increased relatedness density boosted local competition for returns to high-value skills. We find that relatedness density, and more so high-income relatedness density, is associated with a decreased likelihood of such outcomes, indicating the prevalence of the opportunity-creating channel (*Table A7*).

Conclusions

An evolutionary perspective on regional structural change has been forged in the EEG literature during the past two decades through the study of economic diversification, complexity and technological change in regions. Moving forward, we see a critical challenge for EEG to connect these insights with increasingly pressing intra- and inter-regional income inequalities as well as to better understand how the evolution of local economies creates opportunities and constraints, and for whom. To contribute to this agenda, the aim of the present paper was to provide empirical evidence concerning the role of changing local labour market structure in enabling workers to escape or constraining them from escaping low-wage jobs (defined as combinations of industry and occupation).

Our main findings from Swedish local labour markets for the period 2005-2012 indicate that, as regional economies evolve, branching that entails more high-income jobs that share labour pooling with existing low-wage jobs in a region increases the likelihood of workers escaping these low-wage jobs. Hence, regional diversification that is at the same time widening the set of available skill-related high-income jobs for low-wage workers unlocks upward mobility possibilities for them. If we assume that high-income jobs also correspond with high-productive activities (*Kemeny and Storper, 2015*), this would in turn entail a micro-mechanism through which structural change that builds on existing capabilities can take place. As structural change in the EEG literature is not only assessed through the lens of relatedness but also that of upgrading (*e.g.,* by diversification into more complex activities or technologies), our findings add that related diversification can bring about local labour market upgrading in the form of escaping low-wage jobs and potentially even counteracting polarization. These findings also contribute to the low-wage literature by going beyond strict individual-specific explanations and instead quantifying in detail the regional employment structure in relation to jobs and industries (*cf. Avent-Holt et al., 2020*).

Moreover, there is no spatially uniform way in which the career advancement of workers in low-wage jobs can be facilitated. Our descriptive evidence indicates an urban premium in the benefits of relatedness density. However, metro regions tend to have higher relatedness density at the upper end of the distribution, while also having jobs with low levels of relatedness density. This indicates much greater heterogeneity in the probabilities of upward mobility in a metropolitan setting as well as that local opportunities may be scarce even in a thicker labour market, hence explaining the mechanisms of previously identified polarization in diverse metro regions *(Henning and Eriksson, 2021)*. This finding also advances previous accounts mainly stressing that the thickness of urban labour markets in comparison to more rural labour markets promotes career advancement (*Puga, 2010; Culliney, 2017; Grimes et al., 2019*).

Taken together, these findings have clear policy implications. For example, the current Smart Specialization agenda in the EU emphasizes that regional economies should upgrade and diversify around core competencies. Our findings suggest that, when such upgrading is firmly connected to low-wage work in the region, this could also increase the potential for labour market upgrading within the existing pool of labour. This can be contrasted to any type of STEM-related upgrade, which, if not aligned with existing capabilities, could imply greater adjustment costs for the regional labour market and for workers in unrelated activities, in particular. If there is a potential for low-wage workers to find higher-paid jobs in the process of regional branching without re-skilling, this will (1) make it easier to meet current labour market realignments, (2) be on a par with Smart Specialization initiatives that seldom consider the labour market (*cf. Hane-Weijman et al., 2022*), and (3) hopefully contribute to reducing intra-regional inequalities. This creates some room for place-based policy even in lagging regions in which both job creation, in general, and skill-based links between jobs, occupations and industries should be the focus to assist more vulnerable groups of workers in managing ongoing labour market realignments.

The primary limitation of the present investigation lies in its use of labour flow to establish skill-relatedness between jobs. From a technical perspective, employing this measure may create problems of endogeneity when exploring job transitions. To mitigate this issue, we separated the periods of network construction and analysis in the paper. Ideally, one would use some exogenous method to establish skill-relatedness, such as the O*NET database in the US. However, such survey-based methods also have their drawbacks, as these tend to represent the skill requirements set by employers. In contrast, skill-relatedness on the basis of labour flows tends to capture a broader set of job-related characteristics through the revealed behaviour of workers and has been deployed frequently to assess diversification at both the regional and the firm level (*Neffke and Henning, 2013; Neffke et al., 2018*). Additionally, to our knowledge, existing survey-based skill data are not available at the level of resolution of jobs that we investigate here. We also note that the revealed relatedness approach we used aggregates information of labour flows across geographical settings and labour market segments. This has been shown to hold on average (*Neffke et al., 2017*), but may mask some segments of the labour market that are systematically left behind or unable to change work due to formal barriers. Future studies should therefore conduct more segment-specific assessments of which channels may lead to upward mobility.

Furthermore, the present analysis, by design, is geared towards exploring skill-related options for regions to unlock better-paid jobs for workers, and as such it does not deal with the role of unrelated diversification in escaping low-wage jobs. We feel this is a critical question that goes beyond the confines of the present paper and should be taken up in future research. Unrelated diversification, and the different types of agents that induce it, are high on the agenda of research in EEG (*Boschma, 2017*). Recent studies have shown that new establishments by entrepreneurs (*Neffke et al., 2018*) and foreign-owned firms (*Elekes et al., 2019*) tend to create employment in more unrelated economic activities. It is unclear, however, whether and how these instances of unrelated diversification create welfare effects and career opportunities for workers, in general, and upgrading of the job structure, in particular. More broadly, the channel of labour pooling between skill-related low- and high-wage jobs explored in the present paper cannot be considered a sole or sufficient condition of escaping low-wage jobs, as indicated by the relatively low amount of variance explained by the models.

Notwithstanding these limitations and open questions, we argue that the findings put forward here offer, hitherto lacking, robust and high-resolution insights into the evolution of local labour markets, and how it creates economic opportunities and constraints for workers.

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Appendix

Table A1. Pooled descriptives of all workers and the low-wage sample 2006-2012.

	All workers	**Workers in low-wage jobs**		
		All	**Upward**	**Remaining**
Upward		3%		
Related density to high-income jobs	0.154	0.077	0.124	0.074
Population density	88	82	91	82
Metro	50%	45%	53%	45%
Larger centre	37%	39%	34%	39%
Smaller centre	11%	12%	9%	12%
Other smaller region	3%	4%	3%	4%
Employment rate	43%	43%	43%	43%
Mean size of workplace	8	8	8	8
Share of high-income jobs	38%	38%	38%	38%
Regional job size	3089	3771	2183	3826
Age	42	41	38	42
Income (1000 SEK)	331	267	309	266
Female	49%	56%	47%	57%
Higher education	32%	31%	32%	31%
Nordic	91%	89%	93%	89%
EU & Global west	2%	2%	2%	2%
Global south	7%	9%	5%	9%
Same employer	78%	78%	66%	78%
Stayer	90%	90%	87%	90%
ISCO (1-digit)				
Managers	6%	0%	0%	0%
Professionals	19%	0%	1%	0%
Technicians and associate professionals	20%	14%	17%	14%
Clerical support workers	9%	18%	28%	18%
Service and sales workers	19%	44%	25%	45%
Skilled agricultural. forestry and fishery workers	1%	2%	1%	3%
Craft and related trades workers	9%	5%	8%	5%
Plant and machine operators. and assemblers	11%	6%	11%	6%
Elementary occupations	5%	10%	8%	10%
NACE (main division)				
Human health and social work activities	16%	27%	11%	28%
Wholesale and retail trade; repair of motor vehicles and motorcycles	14%	18%	22%	18%
Education	12%	15%	10%	15%
Manufacturing	16%	9%	14%	9%
Accommodation and food service activities	3%	6%	3%	6%
Remaining sectors	37%	22%	38%	21%
N (worker-year)	22,149,004	14,186,400	463,067	13,723,333
N (worker)	4,473,570	3,246,832	444,300	3,134,947

Table A2. Examples of high and low relatedness density to high-income jobs.

Job (industry × occupation)	$HI.RD$
Stockholm	
65.242: Legal professionals in Insurance, reinsurance and pension funding, except compulsory social security	0.957
92.213: Computing professionals in Gambling and betting activities	0.893
92.123: Other specialist managers in Gambling and betting activities	0.842
65.213: Computing professionals in Insurance, reinsurance and pension funding, except compulsory social security	0.825
62.121: Directors and chief executives in Computer programming, consultancy and related activities	0.821
...	...
96.912: Helpers and cleaners in Other personal service activities	0.036
01.513: Personal care and related workers in Crop and animal production, hunting and related service activities	0.029
96.932: Manufacturing labourers in Other personal service activities	0.026
78.912: Helpers and cleaners in Employment activities	0.021
85.513: Personal care and related workers in Education	0.010
Umeå	
86.221: Life science professionals in Human health activities	0.437
72.122: Production and operations managers in Scientific research and development	0.379
86.211: Physicists, chemists and related professional in Human health activities	0.344
85.211: Physicists, chemists and related professional in Education	0.326
85.122: Production and operations managers in Education	0.317
...	...
84.912: Helpers and cleaners in Public administration and defence; compulsory social security	0.007
01.513: Personal care and related workers in Crop and animal production, hunting and related service activities	0.005
96.522: Shop and stall salespersons and demonstrators in Other personal service activities	0.005
01.913: Helpers in restaurants in Crop and animal production, hunting and related service activities	0.001
96.412: Numerical clerks in Other personal service activities	0.001
Åsele	
35.131: Managers of small enterprises in Electricity, gas, steam and air conditioning supply	0.254
49.131: Managers of small enterprises in Land transport and transport via pipelines	0.173
49.121: Directors and chief executives in Land transport and transport via pipelines	0.171
31.131: Managers of small enterprises in Manufacture of furniture	0.165
01.131: Managers of small enterprises in Crop and animal production, hunting and related service activities	0.161
...	...
47.512: Housekeeping and restaurant services workers in Other retail sale of new goods in specialised stores	0.003
47.513: Personal care and related workers in Other retail sale of new goods in specialised stores	0.002
47.912: Helpers and cleaners in Other retail sale of new goods in specialised stores	0.002
82.422: Client information clerks in Office administrative, office support and other business support activities	0.001
78.419: Other office clerks in Employment activities	0.000

Note: the table indicates jobs for each example region, having the highest and lowest nonzero relatedness density to high-income jobs in 2006. 3 out of 883 LQ > 1 jobs had 0 such relatedness density in Stockholm, 1 out of 473 in Umeå, and 9 out of 177 in Åsele.

Table A3. The share of low-wage connections among the most frequent low-wage jobs.

Job (industry × occupation)	***N* (person-year)**	**Low-wage share**
87.513: Personal care and related workers in Residential care activities	1,300,947	0.94
47.522: Shop and stall salespersons and demonstrators in Retail trade, except of motor vehicles and motorcycles	1,109,737	0.93
86.513: Personal care and related workers in Human health activities	719,051	0.84
85.513: Personal care and related workers in Education	589,246	0.94
85.331: Pre-primary education teaching associate professionals in Education	587,272	0.86
85.233: Primary education teaching professionals in Education	587,172	0.74
49.832: Motor-vehicle drivers in Land transport and transport via pipelines	575,916	0.78
86.323: Nursing associate professionals in Human health activities	416,377	0.65
88.513: Personal care and related workers in Social work activities without accommodation	313,669	0.89
41.712: Building frame and related trades workers in Constructions of buildings	230,843	0.79

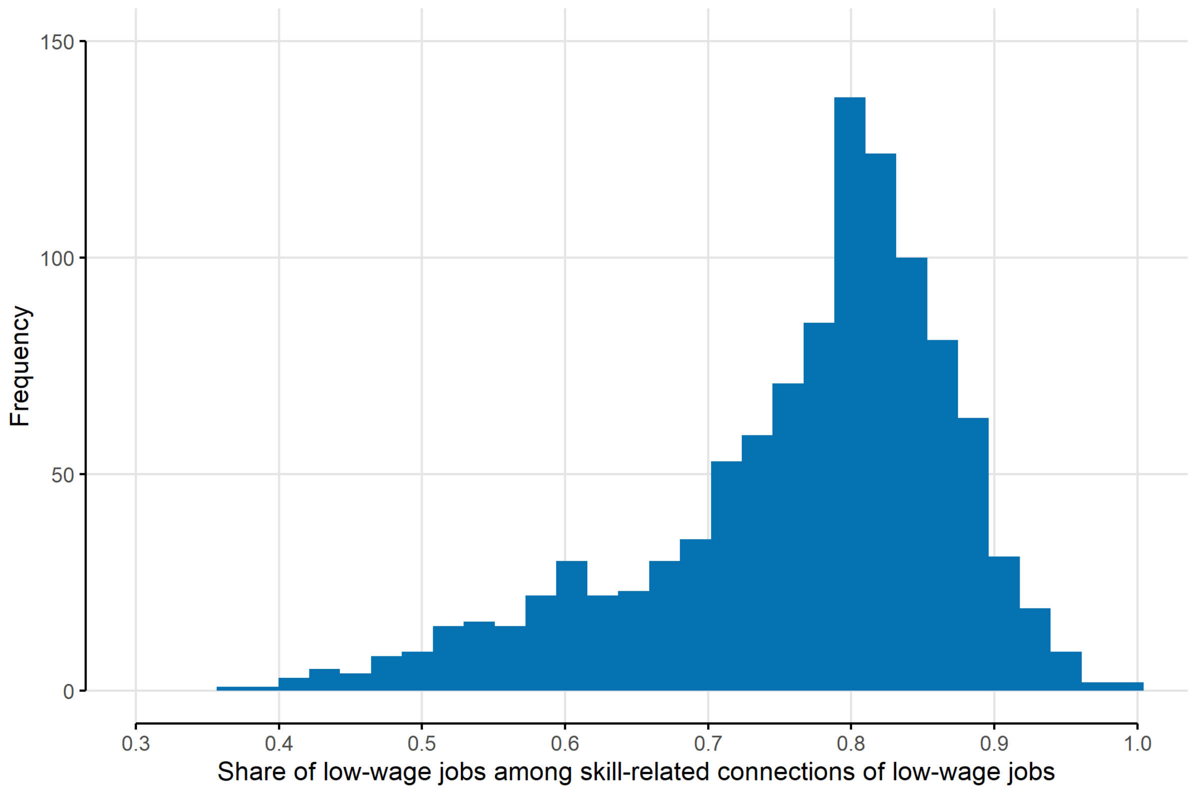

Figure A1. Share of low-wage jobs among skill-related connections of low-wage jobs.

Table A4. Variable description and correlation matrix on all low-wage workers remaining in region 2006-2012.

Variable	Description	Mean	Standard deviation	
(1) Into top 2	Dummy = 1 if transition from jobs in 3 lowest income groups to jobs in income groups 4-5.	0.03	between: within:	0.19 0.13
(2) RD	Relatedness density to all jobs ($t-1$).	0.40	between: within:	0.12 0.04
(3) $HI.RD$	Relatedness density to high-income jobs ($t-1$).	0.08	between: within:	0.07 0.02
(4) AGE	Age of worker ($t-1$).	41.9	between: within:	12.9 1.7
(5) ln $INCOME$	*Ln* yearly income received from work in 1000s SEK ($t-1$).	5.51	between: within:	0.48 0.23
(6) $PCT.HINCJOB$	Share of high-income jobs in region (t – 1)	38.4	between: within:	0.02 0.01
(7) ln $POPDENS$	*Ln* number of persons (total population) per square km in region ($t-1$).	4.01	between: within:	1.07 0.13
(8) $PCT.WORKAGE$	Share of employed persons of all population in region aged 18-64 ($t-1$).	43.0	between: within:	0.03 0.01
(9) $AVG.WPSIZE$	Average workplace size in region ($t-1$).	8.42	between: within:	0.85 0.22
(10) ln $JOBSIZE$	*Ln* number of workers in job-region ($t-1$).	6.44	between: within:	2.12 0.69

Correlation matrix

	(1)	**(2)**	**(3)**	**(4)**	**(5)**	**(6)**	**(7)**	**(8)**	**(9)**	**(10)**
(1)	1.00									
(2)	0.04	1.00								
(3)	0.11	0.54	1.00							
(4)	-0.05	-0.06	0.04	1.00						
(5)	0.01	0.01	0.22	0.22	1.00					
(6)	0.03	0.29	0.22	-0.06	0.01	1.00				
(7)	0.03	0.35	0.23	-0.06	0.01	0.72	1.00			
(8)	0.05	0.30	0.25	-0.07	0.01	0.51	0.46	1.00		
(9)	0.01	-0.14	-0.03	-0.01	0.01	0.28	0.06	0.25	1.00	
(10)	-0.07	0.24	-0.03	-0.03	-0.03	0.46	0.50	0.35	0.01	1.00

Table A5. Marginal effects on standardized variables for the probability of upward mobility from model *M2* and *M3* of *Table 3*.

LHS (sample)	**(1)** Into top 2 (all LW)	**(2)** Into top 2 (all LW)
RD_{t-1}	0.001*** (0.001)	
$HI.RD_{t-1}$		0.011*** (0.000)
AGE_{t-1}	0.083*** (0.000)	0.083*** (0.000)
$\ln INCOME_{t-1}$	0.005*** (0.000)	0.005*** (0.000)
$PCT.HINCJOB_{t-1}$	0.002*** (0.000)	0.002*** (0.000)
$\ln POPDENS_{t-1}$	0.005*** (0.000)	0.003*** (0.001)
$PCT.WORKAGE_{t-1}$	0.009*** (0.000)	0.009*** (0.000)
$AVG.WPSIZE_{t-1}$	-0.003*** (0.000)	-0.002*** (0.000)
$\ln JOBSIZE_{t-1}$	-0.008*** (0.000)	-0.007*** (0.000)
N (worker-year)	13,759,534	13,759,534

Notes: standardized variables; standard errors in parentheses; * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Table A6. Regression models on the within-regional career-mobility of low-wage workers 2006-2012 (sensitivity analysis).

LHS (sample)	**(7)** Upward (<60% median wage)	**(8)** Into 4th (all LW)	**(9)** Into 5th (all LW)	**(10)** Into top 2 (1 mv. per plant)	**(11)** Into top 2 (constant occ.)	**(12)** Into top 2 (constant ind.)	**(13)** Into top 2 (mv. to new plant)	**(14)** Income change (all LW)	**(15)** Into top 2 (all LW)
$HI.RD_{t-1}$	0.045***	0.050***	0.020***	0.139***	0.452***	0.275***	0.284***	0.244***	1.278***
	(0.003)	(0.002)	(0.001)	(0.015)	(0.017)	(0.018)	(0.011)	(0.004)	(0.092)
$WP.CHANGE_{t-1}$								0.017***	
								(0.001)	
$HI.RD_{t-1} \times WP.CHANGE_{t-1}$								0.052***	
								(0.003)	
AGE_{t-1}	0.003***	0.005***	0.002***	0.008***	0.005***	0.042***	0.017***	0.014***	1.157***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.001)	(0.000)	(0.000)	(0.002)
$\ln INCOME_{t-1}$	-0.380***	0.005***	0.004***	0.010***	0.002**	0.100***	0.010***	-0.783***	1.192***
	(0.001)	(0.000)	(0.000)	(0.002)	(0.001)	(0.004)	(0.001)	(0.001)	(0.011)
$PCT.HINCJOB_{t-1}$	-0.000	0.054***	0.044***	0.195***	0.200**	0.255	0.350***	0.012	0.393
	(0.016)	(0.010)	(0.005)	(0.059)	(0.093)	(0.219)	(0.082)	(0.020)	(0.289)
$\ln POPDENS_{t-1}$	0.009***	0.002***	0.002***	-0.009***	-0.009*	-0.015**	-0.011***	0.014***	1.175***
	(0.001)	(0.000)	(0.000)	(0.003)	(0.004)	(0.007)	(0.003)	(0.001)	(0.024)
$PCT.WORKAGE_{t-1}$	0.217***	0.176***	0.085***	0.249***	0.232**	0.762***	0.418***	0.490***	60.380***
	(0.015)	(0.009)	(0.006)	(0.063)	(0.095)	(0.174)	(0.065)	(0.020)	(29.688)
$AVG.WPSIZE_{t-1}$	-0.003***	-0.002***	-0.001***	-0.004*	-0.009***	-0.003	-0.001	-0.006***	1.008
	(0.001)	(0.000)	(0.000)	(0.002)	(0.003)	(0.006)	(0.002)	(0.001)	(0.017)
$\ln JOBSIZE_{t-1}$	-0.002***	-0.002***	-0.001***	-0.005***	0.001***	0.007***	-0.003***	-0.000	0.893***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.001)	(0.000)	(0.000)	(0.003)
Constant	1.940***	--0.294***	-0.143***	-0.408***	-0.231***	-2.322***	-0.879***	3.553***	
	(0.009)	(0.005)	(0.003)	(0.031)	(0.045)	(0.098)	(0.036)	(0.011)	
Worker FE	YES	YES	YES	YES	YES	YES	YES	YES	YES
Year FE	YES	YES	YES	YES	YES	YES	YES	YES	YES
Region FE	NO	NO	NO	NO	NO	NO	NO	NO	NO
N (worker-year)	13,759,534	13,759,534	13,759,534	1,679,443	843,903	845,551	1,790,559	13,759,534	1,125,089
n (worker)	3,199,126	3,199,126	3,199,126	1,155,862	664,995	714,422	1,209,668	3,199,126	296,686
Within R^2	0.181	0.008	0.004	0.013	0.022	0.093	0.028	0.432	
Log likelihood									-305,146

Notes: *Models 7* to *14* report results from fixed effect linear probability models, *Model 15* reports results (odds ratios) from conditional logit model; standard errors in parentheses; * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Table A7. Potential adverse outcomes from high-income relatedness density.

LHS (sample)	**(1)** Left region (all LW)	**(2)** Left region (all LW)	**(3)** Into bot. 3 (all HW)	**(4)** Into bot. 3 (all HW)
RD_{t-1}	-0.015*** (0.001)		-0.003** (0.001)	
$HI.RD_{t-1}$		-0.035*** (0.002)		-0.029*** (0.001)
AGE_{t-1}	0.000*** (0.000)	0.000*** (0.000)	0.006*** (0.000)	0.006*** (0.000)
$\ln INCOME_{t-1}$	-0.017*** (0.000)	-0.017*** (0.000)	-0.017*** (0.000)	-0.017*** (0.000)
$PCT.HINCJOB_{t-1}$	-0.155*** (0.019)	-0.151*** (0.019)	0.083*** (0.017)	0.072*** (0.017)
$\ln POPDENS_{t-1}$	-0.020*** (0.001)	-0.020*** (0.001)	0.004*** (0.001)	0.006*** (0.001)
$PCT.WORKAGE_{t-1}$	0.015 (0.019)	0.017 (0.019)	-0.044*** (0.011)	-0.010 (0.011)
$AVG.WPSIZE_{t-1}$	0.002** (0.001)	0.002** (0.001)	-0.000 (0.000)	-0.001*** (0.000)
$\ln JOBSIZE_{t-1}$	-0.002*** (0.000)	-0.002*** (0.000)	-0.003*** (0.000)	-0.003*** (0.000)
Constant	0.253*** (0.009)	0.245*** (0.009)	-0.158*** (0.007)	-0.159*** (0.007)
Worker FE	YES	YES	YES	YES
Year FE	YES	YES	YES	YES
Region FE	NO	NO	NO	NO
N (worker-year)	14,186,400	14,186,400	7,962,604	7,962,604
n (worker)	3,246,832	3,246,832	1,776,318	1,776,318
Within R^2	0.003	0.003	0.009	0.009

Notes: standard errors in parentheses; * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Considerations on using the location quotient as input for relatedness density

At its core the question is what constitutes a "significant" presence of a job in a region, where it may be reasonable to expect benefits to related jobs. LQ, as introduced in *Equation 2* of the main text, compares the observed weight of the job in a local economy to the expectation based on the share of the same job in the national economy. This yields a straightforward cut-off where values above 1, hence exceeding expectation, are considered significant.

However, one can first challenge the idea that for each job the right expectation to use is uniformly 1 (*O'Donoghue and Gleave, 2004*), as it may be possible that "significant" concentration is idiosyncratic to a job. To test this, we followed the approach of *Tian (2013)*, who also employed in a similar robustness check in connection with related diversification of regions in the past (*Cortinovis et al., 2017*). First, we calculate a standardized version of location quotients for each job-region combination in a given year:

$$SLQ_{i,r} = \frac{LQ_{i,r} - \overline{LQ_i}}{std(LQ_i)}$$

Here $LQ_{i,r}$ is the location quotient of job i in location r, $SLQ_{i,r}$ is the standardized version of it, $\overline{LQ_i}$ and $std(LQ_i)$ are the mean and standard deviation of LQ_i across locations. Next, we bootstrap resample the SLQ for each job i by drawing random samples with replacement from the original job-specific set of SLQ values until the bootstrap sample has the same length as the original (*i.e.*, 72 values corresponding to 72 regions in the analysis). This process is repeated up to a total of 1,000 bootstrap samples for each job. We then calculate the 95th percentile for each bootstrap sample and then calculate the mean of the 95th percentiles. This yields a test value that is unique to a job in our analysis, and which is then compared to the critical value (1.64 for one-tailed test) of a standard normal distribution. In this way, we evaluate separately for each job whether it is concentrated "significantly" in a region in a given year. This alternative concentration measure is then used as input instead of LQ in *Equations 3* and *4* in the paper to construct alternative relatedness density measures.

Next, one can argue that it is not the critical mass of related opportunities agglomerating in a region that matters, but the fact that such jobs are present *at all*. To test this alternative approach, we used the relatedness density variable introduced by *Davies and Maré (2021)* to remedy the potential shortcomings of LQ in regional diversification research. In particular they argue that (1) LQ may have extreme concentration values if the share of an activity in the national economy is near zero; (2) LQ ignores variation in the extent of concentration below and above the thresholding and may be sensitive to small perturbations around the threshold; (3) specializations in smaller regions are likely more sensitive to small changes in employment. Their proposed approach relies on the numerator of the location quotient, *i.e.*, the share of employment in a job in a region. The relatedness density measure is calculated as

$$RD_{i,r} = \sum_{i \neq j} \frac{EMP_{j,r}}{EMP_r} SR_{ij}$$

, where $RD_{i,r}$ is the relatedness density around job i in region r, $EMP_{j,r}/EMP_r$ is the local employment share of a job $j \neq i$ and $SR_{i,j}$ is the relatedness between jobs i and j. For high-income relatedness density we add the same indicator variable to the calculation as in *Equation 4* in the main text. This measure takes into consideration even small concentrations of related jobs and increases continuously as such jobs grow in their local employment share. As an additional feature, this measure cannot grow by the decrease of the employment in a given job *in other regions*, hence an increase always corresponds to growing employment within the related segment of the local economy.

Equipped with these alternative relatedness density measures, we repeated our main model calculation and found similar results (see standardized coefficients reported in *Table 2* of the main text).

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