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How do occupational relatedness and complexity condition employment dynamics in periods of growth and recession?

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## How do occupational relatedness and complexity condition employment dynamics in periods of growth and recession?

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**Abstract:** Related diversification has generated considerable interest in policy (smart specialisation) and academic (related branching) circles, linking regional path creation strategies to the capabilities of regions. While previous studies have tended to focus on knowledge- or industry-spaces in regions, we explore the occupation-space. Occupational relatedness and complexity indicators are deployed as independent variables in spatial panel models that account for annual variations in regional employment growth rates in Sweden between 2002 to 2013. Our findings show that in periods of economic expansion, exit from related occupations and entry into complex occupations decreases regional employment growth. These effects are dampened in periods of economic slowdown.

**Keywords:** Related branching, occupation-space, occupational relatedness, complexity, smart specialization, employment growth

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#### Introduction

The process of economic transformation and regional diversification is currently high on the agenda in both academic and policy environments as many regional economies have struggled to renew their competitiveness following recent recessions (Boschma, 2017). As reflected in the current Smart Specialization Agenda within the EU (Foray et al., 2011), there is increasing awareness that existing capabilities condition which economic activities are developed within regions. Recent studies have provided seminal insights on how regions and nations diversify into new products (Hidalgo et al., 2007), industries (Neffke et al., 2011) or technologies (Kogler et al., 2017). A consistent finding is that spatial economic units diversify incrementally along trajectories that are strongly related (complementary) to what is already present in the region, while abandoning activities that are not as well-embedded. Balland et al. (2019) argue that combining complexity indicators with measures of relatedness in a smart specialization framework holds much promise for thinking about regional economic performance. Rigby et al. (2019) operationalize these ideas showing how technological complexity and relatedness impact employment and GDP growth across the EU.

While there is growing interest in the links between relatedness and regional uneven development, much more work is required to understand how these concepts might be deployed across varying domains, in particular, labour-markets (Whittle and Kogler, 2019). Furthermore, how related diversification in one domain might interact with diversification in another domain raises a number of important questions. For example, Autor et al. (2003) make clear that technological changes have important impacts in labour markets. Disruptive innovation has significant implications for long-run regional growth as it fundamentally reshapes the sets of skills and work-tasks that undergird new growth trajectories (Moretti, 2013). How should fast-growth and slow-growth regions manage their place-based human resources and relations in these unsettled environments? How strongly coupled are human-capital and knowledge portfolios over space and time?

Most previous work on relatedness and regional diversification has tended to be output focussed, often disregarding the labour-skills and work-tasks required as inputs in the development of new economic activities. The tendency to focus on what (firms in) regions *produce* rather than on what the (workers in) regions *do*, might bias our understanding of regional transformation since the know-how embodied within groups of workers, alongside the demands generated by new technologies and the geographies they foment, are critical to the long-run fortunes of workers and regions (Boschma and Martin, 2010). This is especially problematic in an age of global integration and changes in transportation and communication technologies that have seen regional economies specializing in specific functions and work-tasks rather than in industries (Baldwin, 2006; Wixe & Andersson, 2017). To better understand the transformative capacity of regions, we need to refocus on the workplace skills and competences that better capture the economic structures that count (Massey, 1984; Thompson & Thompson, 1985; 1987; Markusen, 2004; Florida et al.,2008).

Muneepeerakul et al. (2013), Jara-Figueroa et al. (2018), Farinha et al. (2019) and Davies and Maré (2019) all take up this task, developing innovative variants of an occupation-space to

explore how changes in the employment structure of places and firms impact economic performance. In this paper, we seek to add to this body of work assessing how changes in the mix of occupations impacts regional employment growth in Sweden. Our raw data comprise longitudinal matched employer-employee observations containing geo-referenced information on all workers in the Swedish economy during the period 2002-2013. These data provide a detailed timeline of changes in the occupational structure of all 72 local labour markets in Sweden.

The research presented adds value in three main ways. First, the papers just referenced measure relatedness between occupations by identifying patterns of occupational co-location. Here we take a different tack, following Neffke and Henning (2013) and Neffke et al. (2017) we link occupations from observed worker flows between them. Measuring the "distance" between occupations from worker mobility data rather than co-location data provides a microperspective of the mechanism by which occupations are related. Second, the usual concern with relatedness is supplemented with analysis of the complexity of occupations (Hidalgo and Hausmann, 2009; Davies and Mare, 2019). In this respect we follow the smart specialization model of Balland et al. (2019), seeking to operationalize their framework though using quite different data and operating at a smaller spatial scale. Third, we do not use relatedness to explain regional patterns of entry and exit across occupations. Rather, we seek to show how changes in occupational relatedness and complexity at the regional level are related to the rate of growth of employment. Exploring how this relationship changes over the business cycle is also novel.

The paper is structured as follows. Conceptual motivation for focusing on the structure of occupations to understand shifts in regional employment follows the introduction. The third section outlines the data and the main principles on which we have constructed the Swedish occupation-space and generated measures of the relatedness and complexity of occupations and regions. The fourth section presents descriptive statistics for Sweden's labour-market areas and results from an empirical model linking occupational relatedness and complexity to regional employment growth. The last section offers a brief conclusion.

#### Theoretical framework

There is mounting evidence that over the past few decades, employment, earnings and career trajectories have become much more unstable, at least for those at the less-skilled end of the labour market (Farber, 2008; Hollister, 2012). The combined impacts of technological innovation and the offshoring of jobs within an increasingly integrated global economy have accelerated the fragmentation of commodity production and the geographical separation of work-tasks that had previously tied industries and sets of skills to particular locations (Baldwin, 2006; Jensen and Kletzer, 2010; Autor et al., 2010; Moretti, 2013; Cooke et al., 2019). On top of these longer running trends, the Great Recession exacerbated labour market precarity within the US and much of the EU, especially for younger workers (Ayllon and Ramos, 2017; Lowe, 2018). The future of work and employment is generating increased debate across many parts of the world (see Rani and Grimshaw, 2019), including Sweden (Woolfson et al., 2014).

The lives and deaths of specific kinds of jobs are explored by Hasan et al. (2015) who report

that technical interdependencies within clusters of work-tasks generate job longevity. In this sense they capture aspects of the relatedness between occupations first outlined by Muneepeerakul et al. (2013). Building on the concept of related diversification introduced by Hidalgo et al. (2007) and developed within a regional setting by Neffke et al. (2011) and Boschma et al. (2013), Muneepeerakul et al. (2013) explore a bipartite network of the structure of employment by US urban areas and occupations. They link urban productivity variations to the occupational structure of cities and they report how occupational upgrading is dependent on that structure. Using similar techniques, later papers by Shutters et al. (2015; 2016) examine how US cities transition towards creative economies, providing additional detail to the broad claims of Florida et al. (2008), and showing how economic resilience can be quantified with occupational relatedness measures. An innovative recent paper by Davies and Mare (2019) refines measures of occupational relatedness and complexity using local area data from New Zealand. They report that complex employment practices experienced faster employment growth since 1981, especially in cities with a diverse range of complex activities, but that relatedness had little impact on local employment growth.

While path-breaking in many respects, much of this research on relatedness, calculated through co-location, suffers from some ambiguity in terms of understanding how different occupations, products or industries actually are related to one another (Tanner, 2014). Farinha et al. (2019) embrace this challenge in an occupational context by combining employment and occupation data for US urban areas and distinguishing between occupational relatedness that is based on the similarity of skills, that which is based on complementarity along a value chain, and that which generates local synergies, after Duranton and Puga (2004). They show that all three measures of relatedness influence the entry and exit of specific types of jobs in cities.

A different tack is employed by Neffke and Henning (2013) who derive measures of industry (human capital) relatedness based on worker mobility across sectors. In similar fashion, Hane-Weijman et al. (2018) and Eriksson et al. (2018) exploit a less noisy measure of relatedness based on occupation similarities across industries in Sweden finding that a high degree of occupation-relatedness protects workers from unemployment. Researchers interested in labour market dynamics should be more at ease that this type of measure of relatedness captures common sets of skills and work-tasks. Using measures of occupational relatedness based on the mobility of workers between occupations allows the focus of the investigator to shift away from what regions produce, where the firm is conceptualized as the primary agent of regional evolution, to explore what regions actually do, with a focus on the agency of individual workers (Thompson and Thompson, 1985; Markusen, 2004; Bristow & Healy, 2013; MacKinnon, 2017). There are a number of reasons to support this move. First, as regions tend to be specialized in terms of functions rather than industries (Wixe & Andersson, 2017), the current spatial division of labour is increasingly occupation-specific rather than industry-specific. Second, within industries entrepreneurial efforts are not shared evenly since certain occupations tend to be more entrepreneurial than others (Markusen, 2004). Third, the job commitment of both workers and employers has waned. This implies that the incentives for firms to train the workforce is lower today due to potential risk for poaching (Eriksson & Rodriguez-Pose, 2017). Firms are increasingly dependent on regional labour pools as training tends to be externalized to regional institutions (Eriksson & Lindgren, 2009).

Most research on relatedness is linked to the economic diversification of regional economies, rather than how relatedness (and complexity) impact regional fortunes. However, this is beginning to change. As noted above, Muneepeerakul et al. (2013) link occupational relatedness to urban productivity growth, Davies and Mare (2019) report how occupational relatedness and complexity influence local employment growth, and Balland et al. (2015) show that technological relatedness is a significant dimension of the resilience of regions to recessions. At the national scale, Pinheiro et al. (2018) use product-level data to show that countries diversifying into unrelated activities experience a significant positive growth effect. Within the context of EU development policy, Rigby et al. (2019) report EU cities that developed knowledge stocks in a fashion consistent with the smart specialization framework of Balland et al. (2019) experienced higher rates of growth of employment and GDP. This line of research is extended in the work presented below.

#### **Data and Methods**

To analyse how changes in the mix of occupations within regions influences employment growth, we use individual micro-data from Statistics Sweden. These data record the occupations of individual workers active in the Swedish labour market, their place of work (municipality) and industry affiliation. To define an occupation, the 3-digit level of the Swedish SSYK96 occupation nomenclature is used (broadly consistent with the international ISCO-88). The period of analysis, 2002-2012, is chosen for two main reasons. First, work by Åberg (2013) has identified the years after 2000 as a phase of significant polarization in Sweden, linked to changing occupational structures. Second, a revised occupational classification introduced in 2013 makes longer run comparative analysis difficult.

The data includes all workers with an occupation-code that receive their main income from paid employment. Our focus is on the regional dimension of labour market processes. The spatial units examined are based on functional economic areas (FA-regions) developed by the Swedish Agency for Growth Policy Analysis (see the Swedish Agency 2011 working paper). These are created by aggregating municipalities into 72 FA-regions based on a combination of observed commuting flows and labour market analyses, As shown in previous studies on Sweden (e.g., Boschma et al., 2014), this spatial unit mitigates the risk of spatial autocorrelation as they describe labour-market areas where workers both reside and work.

Before turning to the details of the empirical work, a note on context is warranted. From the early-1950s to the early-1970s Sweden developed a strategy later referred to as the *Swedish model*; welfare politics were put at centre-stage, with large state investments in social reforms, strong unions, a "solidarity-wage" system and low unemployment (Movitz and Sandberg, 2013). This meant a shift in living conditions for the average Swedish citizen. Income differences decreased while consumption increased dramatically among the majority of the population. Beginning in the 1970s as a response to the oil-crises, the political focus shifted and firm profitability was pushed through currency devaluation and stagnating wages. Ultimately,

this led to an overheated market and a major macroeconomic recession at the beginning of the 1990s, when gross domestic product (GDP) fell by 6% and unemployment rose from 1.5% (1989–1990) to 8.2% in 1993 (Magnusson, 2002).

The recession hit the economy hard and it took a long time before Sweden managed to recover the jobs lost since the late-1980s. As in many other advanced capitalist economies (Bristow, 2010), the 1990s also marked the start of a shift in Sweden towards more knowledge-intensive production (in particular services) and more supply-oriented policies as this was assumed to secure the future competitiveness of regional economies. In effect, the long period of regional convergence during the post-war period (Enflo and Henning, 2016) turned into a period of increasing regional divergence in which only 13 of 72 local labour markets have experienced an increase in the total number of jobs since the early 1990s (Eriksson & Hane-Weijman, 2017).

Alongside the growing regional divergence in Sweden has been a significant change in the internal structure of regional economies. Based on Metcalf et al. (2006) the industry-mix and occupation-mix of all Swedish FA-regions (based on the shares of employment in respective 2-digit industry and 3-digit occupation) in 2002 are correlated with the same variables in each subsequent year from 2003 to 2013 (Figure 1). If growth was proportional (i.e., all sectors or occupations in all regions grow at the same rate), these coefficients would be stable over time. However, this is not the case as the two lines are decreasing monotonically over time, meaning that new jobs are created in certain industries/occupations and destroyed in other industries/occupations. Of particular interest for this study is that the correlation of the industry-mix over time is decreasing faster than the correlation of the occupation-mix. This implies that where people work and what they are producing are changing over time, but what people are doing remains more stable.

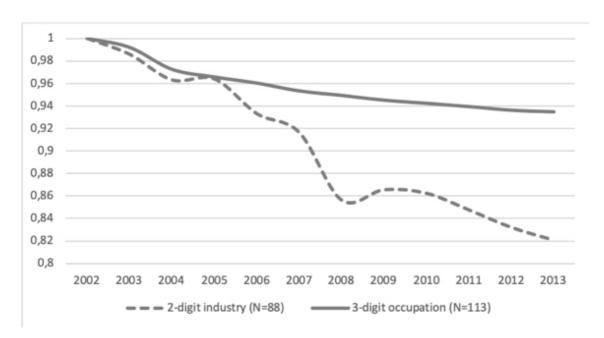
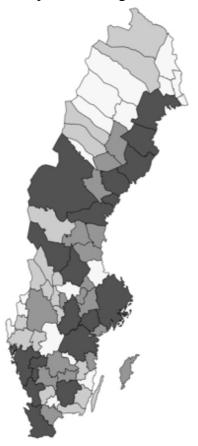


Figure 1: Correlation of industry- and occupation-mix 2002 with each subsequent year

However, this general pattern varies over the regional hierarchy. As depicted in Figure 2, the darkest colours represent the top 25% of occupation-mix correlation 2002-2013 and the lightest coloured regions the lowest 25%. Metropolitan regions (Stockholm in the East, Goteborg in the West, and Malmo in the South) experienced more proportional growth (ca 0.98 correlation) than elsewhere. Apart from those three regions it is the coastal zone between Goteborg and Malmo, and a belt of regions near Stockholm and the Northern coast that have been growing more proportionally, while the greatest structural changes have been occurring in rural and/or more peripheral regions.

Figure 2: Quartile distribution of structural change in occupation-mix 2002-2013. Darkest colour represents top 25% and lightest colour lowest 25%



Regional trajectories: Distance & direction of regional transformation

The regional branching literature rests upon the idea of change (or transformation) as being related or unrelated in different degrees to the existing economic structure of the region (Boschma, 2017). This framework is operationalized in the following way. First, regional transformation is captured by changes in the occupational specialization of a region. By convention, such changes are measured by temporal shifts in the pattern of regional comparative advantage (RCA). RCA is another term for a location quotient and rendered binary (0/1) depending on whether a region has a higher share of an occupation than the Swedish average. A region (r) is said to be specialized in an occupation (i) at time (t) if

$$\frac{\text{Emp}_{r,i}^{t}/\sum_{i}\text{Emp}_{r,i}^{t}}{\sum_{r}\text{Emp}_{r,i}^{t}/\sum_{r}\sum_{i}\text{Emp}_{r,i}^{t}} \ge 1$$
 (Eq. 1)

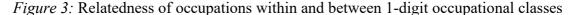
All 112 occupations identified in Sweden's occupational classification (excluding military) are categorized as specialized or not for all functional labour markets each year.

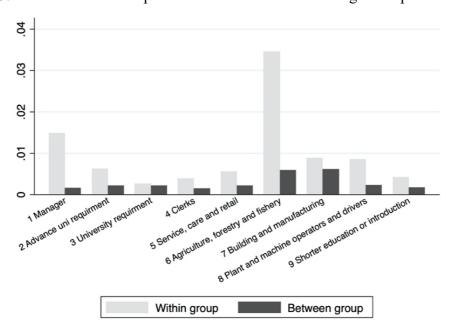
In a second step, the distance or relatedness between occupations is measured using the notion of skill-relatedness based on relative risks (Neffke et al., 2017), where the observed flow from occupation i to j ( $F_{ij}$ ) for the whole study period is divided by the expected flow (the product of all inflows to occupation j and outflows from occupation i, divided by total flows):

$$R_{ij} = \frac{F_{ij}}{(\sum_{k \neq j} F_{kj} * \sum_{k \neq i} F_{ik})/F}$$
 (Eq. 2)

The relatedness values between occupations range from 0.00001 to 0.82606 with a mean of 0.00314. High relatedness values indicate that two occupations are closely related or that the worker flows between these occupations are larger than expected. High relatedness values are indicative of skill and task-based similarities between occupations. Low relatedness values indicate that a pair of occupations have little overlap in terms of their skills-base.

Figure 3 displays the mean occupational relatedness values within and between each respective 1-digit (aggregate) occupation group. The figure makes clear that a majority of all worker flows occur across occupations that are contained within a 1-digit class. In general, managers and occupations within agriculture, forestry and fishing tends to have the strongest connections within the same occupation-class, while building and manufacturing and occupations requiring a generic university education tend to have relatively more inter-class connections. Relatedness values used in the remainder of the paper are normalized.





In a third step of the analysis, the complexity values of the occupations are generated. We use the complexity measure of reflections proposed by Hidalgo and Hausmann (2009) for products and adapted in matrix form by Balland and Rigby (2017) for city-technology matrices. The complexity measure combines two components: (i) the diversity of the regional occupation-mix, and (ii) the ubiquity of occupations. An occupation is thus defined as complex if relatively few regions are specialized in that particular occupation and if this relatively rare occupation is typically found (RCA=1) in regions that are diverse (Balland, 2017). The complexity values for occupations are readily constructed from a bipartite network of regions and occupations represented in matrix form in a binary adjacency matrix M that has dimension 72x112. After row standardizing matrix M along with its transpose  $M^T$  we find the product  $D = M^T * M$ . The second eigenvector of the square-matrix D yields the complexity values for all 112 Swedish occupations. Tables A1 and A2 in the Appendix show the most/least complex occupations and to which other occupations they are most highly related.

#### The occupation-space and the complexity of Swedish occupations

Figure 4a shows the Swedish occupation space, where nodes represent different occupations. The size of the nodes indexes their relative complexity, while the relatedness values locate the nodes. Nodes that are relatively close to one another have vectors of relatedness values that are highly correlated. Nodes that are distant have less correlated relatedness vectors. Neighbouring nodes thus represent occupations that have many similarities in terms of skills and specific work-tasks. For specific regions within Sweden, the location of nodes in the occupation-space and their complexity are held constant, but only those nodes for which RCA>1 in the respective regions are displayed. The node colours represent the 1-digit aggregate occupation classes as listed in Figure 4a.

By comparing a metropolitan region (Stockholm) with a large regional centre containing a university (Umea), and with a small manufacturing region in the north of Sweden (Kramfors) in Figures 4b-d we find interesting differences across the occupation-spaces. Stockholm, for example, has relatively more specializations than smaller regions, and those specializations focus on different forms of management (dark green nodes), on occupations requiring advanced university educations (e.g., life-science, social science, computing professions and legal professions), but also on service occupations like cashiers and housekeepers. The occupationmix of a university region like Umea resembles Stockholm in many ways apart from the fact that the complexity of occupational specializations tends to be lower, and that relatively more specializations occupy the lower right part of the occupation-space (different forms of machine operators), signalling relatively more manufacturing jobs within that region. Lastly, Kramfors' specializations mainly circle around different forms of machine- and plant-operators but also public-finance occupations in education and health. Looking across the regional data for Sweden, in general, the larger a region in terms of population, the more complex (size of nodes) are the occupations in which the region is specialized (pairwise correlation between average complexity and regional size = 0.82). Moreover, it is clear from the comparisons that the occupational-mix of different regions vary in terms of the skills and competences employed in the production of goods and services.

Figure 4a: Sweden's occupation-space. Below (b-d) are the same space but are examples of some regions' occupational specializations over the regional hierarchy

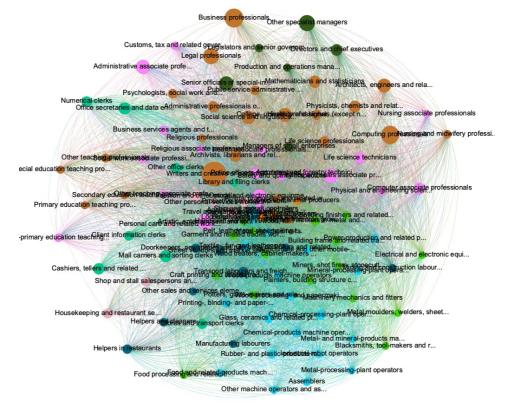


Figure 4b: A metropolitan occupation space (Stockholm)

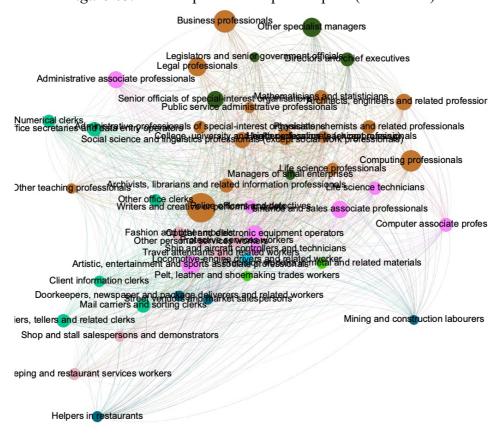


Figure 4c: A larger regional center's occupation space (Umeå)

Legislators and seni@government officials Production and operations managers Psychologists, social work and related professionals Physicists, chemists and related professionals Social science and PHOGOSTHESI YOUTH Nursing and midwifery profes Religious professionals Life science professionals Religious ateatrates professionals (except nursing)
Social work associate professionals and related information professionals cience technicians ition teaching professionals Safe North And Aspect of technicians Library and filing clerks Secondary ed Others ( The claims of the personal Self legiconic equing professionals Other personal Self legiconic equing professionals Other personal Self legiconic equipment of the personal Self legi Personal California Personal Worker Motor-vehicle drivers Power-production and related plant operators teaching associate informational lerks Doorkeepers, newspaper and package deliverence and deliverence and sorting clerks. Mail carriers and sorting clerks Wood-products machine operators

Whose and stall salespersons and demonstrators Wood-processing- and papermaking-plant operators Metal moulders, welders, sheet-metal workers, structural-metal preparers as Chemical-products machine operators Helpers in restaurants

Figure 4d: A peripheral region's occupation space (Kramfors)

Legislators and seniongovernment officials

Assemblers

Religious professionals Managers of small enterprises Other teaching vorafessionals professionals ication teaching professionals Police of get property of petry technicians Secondary education teaching professionals her models recovered and arriver own description teaching professionals of the personal services workers and arriver and related abovers and related abovers and related abovers and related workers workers workers workers workers are related to the personal services. related abouters and related trades workers and and related materials Pelt, leather and Motor vekinget cardes sworkers Building frame and that entrade elated plant operation Street vendors and marketisultereteron ther mobile-plant operators Electrical and electronic equipmer Other sales and services elementary occupations papermaking plant of the fitters Metal moulders, welders, sheet-metal workers, structural-metal lousekeeping and restaurant services workers Helpers and cleaners Metal- and mineral-products machine operators
Blacksmiths, tool-makers and related trade
Rubber- and plastic-products stack in both and plastic products machine and plastic products machine operators. Food processing and related trades workers Assemblers

Table 1 lists the complexity ranking for Swedish labour-market areas in 2002 and 2012, based on the aggregation of specialisations. Unsurprisingly, the three metropolitan regions dominate the complexity ranks for both years – as these labour markets contain a relatively high share of workers in the most complex occupations (see Table A1). There is considerable stability in the labour-market complexity ranks over time. Only 4 labour markets that were in the top-10 ranking in 2002 fell out of the top-10 ranks in 2012 and three of these regions did not fall very far. Karlskoga is an exception, falling from rank 9 in 2002 to rank 42 in 2012, largely because the region exited occupations with above average complexity after 2002 (see Figure 5b). The four regions moving into the top 10 complexity ranks by 2012 did not climb very far. Arjeplog though, climbed from rank 25 in 2002 to rank 9 in 2012. Arjeplog has exited even more complex occupations than Karlskoga since 2002, but has also entered into a number of other high complexity occupations.

Table 1: Complexity ranking for Swedish labour-market areas, 2002 and 2012

Top-ranks	Ranking 2002	Ranking 2012
1	Stockholm	Stockholm
2	Goteborg	Goteborg
3	Malmo	Malmo
4	Sundsvall	Almhult
5	Almhult	Sundsvall
6	Boras(12)	Haparanda(16)
7	Umea	Gotland(21)
8	Vaxjo(15)	Umea
9	Karlskoga(42)	Arjeplog(25)
10	Ostergotland(22)	Kiruna(18)

Note: Terms in parentheses show ranks for other period

It is instructive to explore how Swedish regions have adjusted their occupation-mix over time, in terms of both relatedness and complexity. These are questions at the core of the smart specialization literature within the EU (Foray et al. 2009; McCann and Ortega-Argiles, 2015; Balland et al., 2019). The answers to these questions are revealed in Figure 5 that maps Swedish labour markets in a "smart-specialization space" for occupational entry and exit during the study period (see Rigby et al., 2019). The entry space of Figure 5a indicates whether regional labour markets have tended to add specialization in occupations that are above/below average in terms of relatedness and complexity relative to the region's base-year occupational structure. The exit space of Figure 5b provides the same information for labour-markets in terms of losing specialization in particular occupations.

Figure 5a: Smart specialization spaces (entry) for Swedish labour markets, 2002-2012

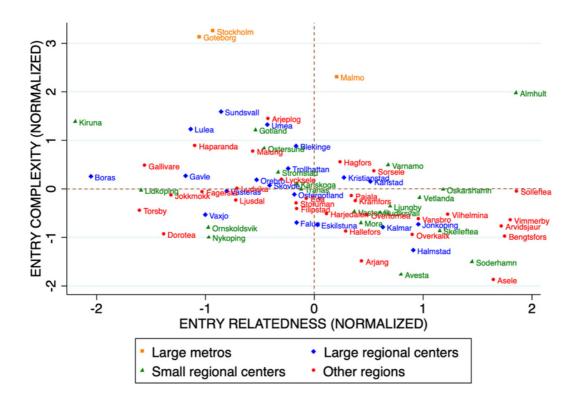
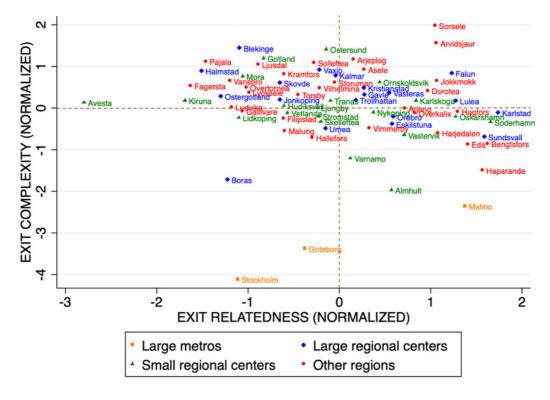


Figure 5b: Smart specialization spaces (exit) for Swedish labour markets, 2002-2012



The entry space in Figure 5a shows that the three large metropolitan areas of Stockholm, Goteborg and Malmo, developed specializations in occupations with complexity values greater than their respective regional averages over the period 2002 to 2012. In Stockholm and Goteborg, these new occupations were relatively unrelated to the existing skill- and work-task mix of the regions, while in Malmo entry into more complex occupations was more consistent with the region's existing occupational structure. Smaller labour market areas in Sweden are widely distributed over the four quadrants of the smart specialization space and no clear patterns in terms of entry into occupations by level of complexity and relatedness can be made. For Sweden's larger regional centres, the three northernmost areas (Sundsvall, Umea and Lulea) have all been adding occupations with relatively high levels of complexity, while a region like Halmstad has moved in the opposite direction.

The situation is not that different when we turn to exit and the loss of specialization in occupations across Swedish regions (Figure 5b). More than half of Sweden's labour market areas have been losing specialization in occupations that are more complex than the average (these are the locations above the dashed line on the complexity axis). The top-right quadrant of the exit space also reveals that a good number of these labour market areas have also been losing specialization in occupations that are closely related to their respective occupational cores. This pattern is inconsistent with a strategy of building competitive advantage around existing capabilities and we suspect that it reflects a set of dynamics driven, at least in part, by the recession in 2008. The three large metro areas have moved out of specializations with lower complexity than the average, and in the cases of Stockholm and Goteborg, these specializations were also in occupations with lower relatedness to the regional occupational cores.

#### How does the occupation-space condition regional development?

Armed with the information from Figure 5, we now seek to understand whether Swedish regions that adjusted their occupational mix in a fashion consistent with the broad tenets of smart specialization – entering more related and complex occupations and exiting less related and complex occupations – have performed better or worse than average in terms of employment growth over the period 2002-2013. To examine this question a spatial panel is constructed where the dependent variable is the annual rate of employment growth for each Swedish labour-market for the years indicated. The key independent variables are annual shifts within each region of the relatedness (RLTDN) and complexity (COMPLEX) of occupations added to the region (ENTRY) and removed from the region (EXIT). The analysis focuses upon whether occupational relatedness or complexity is the more important driver of shifts in regional employment, and on how they impact employment growth rates in periods of general economic expansion (pre-2008) and in periods of crisis (post-2008). For this we employ a recession dummy variable and a set of interaction terms (see list of variables in Table 2).

Additional covariates are also added. These are the share of employment in the public sector (PUBLIC SHARE), the manufacturing employment share (MANUF SHARE), as well as a dummy of 1 if the year is 2008 or higher, to assess the impact of the financial recession. The share of public sector employment is motivated by the relatively strong presence of the public sector in Sweden in some (mainly less prosperous) regions, this part of the economy also

follows somewhat different logics and tends to have lower income levels than other sectors. The opposite could be said about manufacturing, which dominates employment in many of the smaller regions. Because the number of regional specializations (occupations with RCA = 1) varies with labour market size, the number of occupational specializations in each region (N\_RCA) is added as a control for region size. Finally, as we are examining a growth model, the lagged level of regional employment (EMPLOYMENT) is included. The coefficient on this variable provides evidence of catch-up, or mean-reversion in the data. All variables and descriptive statistics are found in Table A3 in the Appendix. Collinearity is not high between most of our independent variables and should therefore not distort our interpretation.

Since our data has a panel structure (i.e., yearly repeated regional observations), a fixed-effect panel model is estimated. The relatedness and complexity variables measure changes between time-periods and because all the continuous independent variables are lagged one period, the total number of observations is 720 (72 regions across 10 years). The fixed effect model specification permits investigation of within-region shifts in independent variables and their impact on employment growth while negating concerns with unobserved regional attributes (e.g., local institutions or labour market conditions), at least those constant over time. Hausman tests support our use of fixed over random model specifications. However, we face other concerns with estimation. Our observational units are regions so we must take explicit account of spatial dependence in the data. Further, almost all economic variables are correlated and so endogeneity is a real concern. We do not explicitly incorporate instrumental variables for no reasonable instruments are available and the time-series is not long enough to utilize deep lags of the independent variables. We do lag the continuous explanatory variables one year to dampen concerns with simultaneity bias. The recession dummy is not lagged. Finally, a full-set of year-dummies are included in the model to control for time-specific heterogeneity that is not place-specific (e.g., business cycles) and which is shorter in duration than the multi-year recession dummy.

The geography of Sweden's 72 labour-market areas was captured using inverse distance weights between all regions. These distance weights were built from coordinates locating the centroid of each area. Calculating the Moran index revealed no significant spatial autocorrelation in employment growth rates for the years investigated. Furthermore, employing the spatial linear model (splm) package in R, there was no evidence of significant spatial lag or error terms in spatial panel models of annual employment growth rates using a base model consistent with those reported in Table 2. We do not discuss spatial dependence further.

Table 2 presents results from estimating 5 different models. Models 1-4 are estimated across all non-metropolitan regions (excluding Stockholm, Goteborg and Malmo). Model 5 has the same specification as Model 4 but includes all regions. Models 1-3 examine the effects of the core independent variables, but do not separate those effects across growth and recession periods. Models 4 and 5 explicitly separate the impact of the relatedness and complexity variables across growth and recession periods. The interaction terms in Models 4 and 5 combine the recession dummy with each of the core independent variables – entry relatedness (NRD), exit relatedness (XRD), entry complexity (NCX) and exit complexity (XCX). Separating the

performance of smaller labour-market areas with metropolitan regions is important. There is more inertia to the occupational structure in the larger metropolitan areas that might dampen the influence of dynamics in smaller regions. We do not wish our overall results to be driven by processes found only in metropolitan regions that have been characterized as leading to increases in the geographical polarization of employment (Eriksson & Hane-Weijman, 2017) and incomes (Enflo and Henning, 2016). Following Rodriguez-Pose (2018), one of our main concerns is to understand processes of growth outside the largest city-regions.

Across all the models in Table 2, the recession dummy has the anticipated negative sign, indicating that after 2007, the annual rate of employment growth was lower than it was before 2008. The negative and significant coefficient for lagged employment indicates that smaller labour markets enjoy faster rates of employment growth than larger labour markets. Note that the coefficient on employment is not significant for Model 5 that includes metropolitan regions. While Stockholm's employment growth over the whole study period exceeds the 75<sup>th</sup> percentile for all regions, that for Goteborg and Malmo is below the median. As shares of manufacturing and public-sector workers rise across labour-markets so employment growth slows, significantly so in the case of manufacturing. Changes in the number of specializations found in Swedish labour-markets have no impact on employment growth.

Turning to the core independent variables, Models 1-3 show the influence on the rate of growth of employment of entering and exiting occupations for the study period as a whole. The entry relatedness variable captures the location of labour markets with respect to the X-axis (relatedness) in the entry panel of Figure 5a. The exit relatedness variable captures the location of labour markets on the X-axis in the exit panel, while the entry and exit complexity variables capture the location of Swedish labour markets on the Y-axis in the respective entry and exit panels. The results in Table 2 reveal that entry relatedness, entry complexity and exit complexity have no significant impact on employment growth. However, the coefficient on exit relatedness is negative and significant. This means that as regions exit occupations that are more (less) related to their occupational cores, the rate of growth of employment decreases (increases). This makes sense because regions that abandon occupations central (peripheral) to their labour market capabilities might anticipate negative (positive) economic impacts as they dismantle (consolidate) those capabilities.

Table 2: Fixed-effect models of the influence of occupational structure on the rate of growth of regional employment

ENTRY RLTDN	or regional employment									
(NRD)         (0.0027)         (0.0027)         (0.0081)         (0.0082)           EXIT RLTDN         -0.0065*         -0.0081**         -0.0158**         -0.0173***           (XRD)         (0.0034)         (0.0037)         (0.0075)         (0.0064)           ENTRY COMPLEX         -0.0016         -0.0036         -0.0196*         -0.0138           (NCX)         (0.0043)         (0.0047)         (0.0106)         (0.0111)           EXIT COMPLEX         -0.0022         -0.0049         -0.0038         -0.0040           (XCX)         (0.0060)         (0.0064)         (0.0107)         (0.0075)           RECESSION*         -0.1005*         -0.0996*         -0.1000*         -0.1001*         -0.1189*           RECESSION*NRD         (0.0544)         (0.0543)         (0.0544)         (0.0610)           RECESSION*XRD         -0.0006*         (0.0054)         (0.0076)         (0.0097)           RECESSION*XRD         -0.0007*         -0.0137*         (0.0121**           RECESSION*XCX         -0.0006*         -0.0006*         (0.0057)           RECESSION*XCX         -0.0006*         -0.0006*         -0.0006*           EMPLOYMENT         -0.00000*         -0.0000*         -0.0006*         -0.0006	-	Model 1	Model 2	Model 3	Model 4	Model 5				
EXIT RLTDN	ENTRY RLTDN	-0.0015		-0.0028	-0.0089	-0.0036				
(XRD)         (0.0034)         (0.0037)         (0.0075)         (0.0064)           ENTRY COMPLEX (NCX)         -0.0016         -0.0036         -0.0196*         -0.0138           (NCX)         (0.0043)         (0.0047)         (0.0106)         (0.0111)           EXIT COMPLEX         -0.0022         -0.0049         -0.0038         -0.0040           (XCX)         (0.0060)         (0.0064)         (0.0107)         (0.0075)           RECESSION         -0.1005*         -0.0996*         -0.1000*         -0.1001*         -0.1189*           (0.0544)         (0.0544)         (0.0543)         (0.0544)         (0.0610)           RECESSION*NRD         -         -         -         (0.0097)         0.0032           RECESSION*XRD         -	(NRD)	(0.0027)		(0.0027)	(0.0081)	(0.0082)				
ENTRY COMPLEX (0.0016 -0.0036 -0.0196* -0.0138 (NCX) (0.0043) (0.0047) (0.0106) (0.0111) (EXIT COMPLEX -0.0022 -0.0049 -0.0038 -0.0040 (XCX) (0.0060) (0.0064) (0.0107) (0.0075) (0.0075) (0.0544) (0.0544) (0.0545) (0.0543) (0.0544) (0.0544) (0.0545) (0.0543) (0.0544) (0.0096) (0.0096) (0.0096) (0.0096) (0.0097) (0.009	EXIT RLTDN	-0.0065*		-0.0081**	-0.0158**	-0.0173***				
$ \begin{array}{c ccccccccccccccccccccccccccccccccccc$	(XRD)	(0.0034)		(0.0037)	(0.0075)	(0.0064)				
EXIT COMPLEX (0.0062) -0.0049 -0.0038 -0.0040 (XCX) (0.0060) (0.0064) (0.0107) (0.0075) (0.0075) (0.0054) (0.0544) (0.0544) (0.0545) (0.0543) (0.0544) (0.0544) (0.0610) (0.0097) (0.00	ENTRY COMPLEX		-0.0016	-0.0036	-0.0196*	-0.0138				
$\begin{array}{c ccccccccccccccccccccccccccccccccccc$	(NCX)		(0.0043)	(0.0047)	(0.0106)	(0.0111)				
RECESSION         -0.1005*         -0.0996*         -0.1000*         -0.1001*         -0.1189*           RECESSION*NRD         (0.0544)         (0.0545)         (0.0543)         (0.0544)         (0.0610)           RECESSION*NRD         (0.09545)         (0.0543)         (0.0974)         (0.0032)           RECESSION*XRD         (0.0096)         (0.0096)         (0.0091)           RECESSION*NCX         (0.0076)         (0.0057)           RECESSION*XCX         (0.0121)         (0.0113)           RECESSION*XCX         -0.0000*         -0.0000*         -0.0006         0.0005           EMPLOYMENT         -0.0000*         -0.0000*         -0.0000*         -0.0000*         -0.0000*         -2.92E-06           (5.59E-06)         (5.58E-06)         (5.55E-06)         (5.38E-06)         (-2.46E-06)           MANUF_SHARE         -1.2985*         -1.2998*         -1.2935*         -1.2241*         -1.1908*           (0.7270)         (0.7346)         (0.7317)         (0.7180)         (0.6597)           PUBLIC_SHARE         -0.4213         -0.3913         -0.4408         -0.4206         -0.3960           N_RCA         (0.0023)         (0.0023)         (0.0023)         (0.0023)         (0.0023)         (0.0023) <td>EXIT COMPLEX</td> <td></td> <td>-0.0022</td> <td>-0.0049</td> <td>-0.0038</td> <td>-0.0040</td>	EXIT COMPLEX		-0.0022	-0.0049	-0.0038	-0.0040				
$\begin{array}{c ccccccccccccccccccccccccccccccccccc$	(XCX)		(0.0060)	(0.0064)	(0.0107)	(0.0075)				
RECESSION*NRD       0.0097       0.0032         RECESSION*XRD       (0.0096)       (0.0091)         RECESSION*XRD       0.0137*       0.0121**         (0.0076)       (0.0057)       (0.0057)         RECESSION*NCX       0.0266**       0.0200*         (0.0121)       (0.0113)         RECESSION*XCX       -0.0000*       -0.0000*       -0.0006       0.0005         EMPLOYMENT       -0.0000*       -0.0000*       -0.0000*       -0.0000*       -2.92E-06         (5.59E-06)       (5.58E-06)       (5.55E-06)       (5.38E-06)       (-2.46E-06)         MANUF_SHARE       -1.2985*       -1.2998*       -1.2935*       -1.2241*       -1.1908*         (0.7270)       (0.7346)       (0.7317)       (0.7180)       (0.6597)         PUBLIC_SHARE       -0.4213       -0.3913       -0.4408       -0.4206       -0.3960         (0.3249)       (0.3180)       (0.3281)       (0.3261)       (0.3386)         N_RCA       0.0003       0.0002       0.0003       0.0003       0.0011         (0.0323)       (0.0023)       (0.0023)       (0.0023)       (0.0023)       (0.0023)         CONSTANT       1.8566***       1.8644***       1.8603***       1.86	RECESSION	-0.1005*	-0.0996*	-0.1000*	-0.1001*	-0.1189*				
$\begin{array}{c ccccccccccccccccccccccccccccccccccc$		(0.0544)	(0.0545)	(0.0543)	(0.0544)	(0.0610)				
$\begin{array}{c ccccccccccccccccccccccccccccccccccc$	RECESSION*NRD				0.0097	0.0032				
$\begin{array}{c ccccccccccccccccccccccccccccccccccc$					(0.0096)	(0.0091)				
$\begin{array}{c ccccccccccccccccccccccccccccccccccc$	RECESSION*XRD				0.0137*	0.0121**				
$\begin{array}{c ccccccccccccccccccccccccccccccccccc$					(0.0076)	(0.0057)				
RECESSION*XCX       -0.0006       0.0005         EMPLOYMENT       -0.0000*       -0.0000*       -0.0000*       -0.0000*       -2.92E-06         (5.59E-06)       (5.58E-06)       (5.55E-06)       (5.38E-06)       (-2.46E-06)         MANUF_SHARE       -1.2985*       -1.2998*       -1.2935*       -1.2241*       -1.1908*         (0.7270)       (0.7346)       (0.7317)       (0.7180)       (0.6597)         PUBLIC_SHARE       -0.4213       -0.3913       -0.4408       -0.4206       -0.3960         (0.3249)       (0.3180)       (0.3281)       (0.3261)       (0.3386)         N_RCA       0.0003       0.0002       0.0003       0.0003       0.0011         (0.0023)       (0.0023)       (0.0023)       (0.0023)       (0.0023)       (0.0022)         CONSTANT       1.8566***       1.8644***       1.8603***       1.8673***       1.4954***         (0.03567)       (0.3545)       (0.3544)       (0.3505)       (0.2632)         YEAR FE       YES       YES       YES       YES         R² (WITHIN)       0.2736       0.2715       0.2750       0.2853       0.1398	RECESSION*NCX				0.0266**	0.0200*				
$\begin{array}{c ccccccccccccccccccccccccccccccccccc$					(0.0121)	(0.0113)				
EMPLOYMENT         -0.0000*         -0.0000*         -0.0000*         -0.0000*         -2.92E-06           (5.59E-06)         (5.58E-06)         (5.55E-06)         (5.38E-06)         (-2.46E-06)           MANUF_SHARE         -1.2985*         -1.2998*         -1.2935*         -1.2241*         -1.1908*           (0.7270)         (0.7346)         (0.7317)         (0.7180)         (0.6597)           PUBLIC_SHARE         -0.4213         -0.3913         -0.4408         -0.4206         -0.3960           (0.3249)         (0.3180)         (0.3281)         (0.3261)         (0.3386)           N_RCA         0.0003         0.0002         0.0003         0.0003         0.0011           (0.0023)         (0.0023)         (0.0023)         (0.0023)         (0.0022)           CONSTANT         1.8566***         1.8644***         1.8603***         1.8673***         1.4954***           (0.03567)         (0.3545)         (0.3544)         (0.3505)         (0.2632)           YEAR FE         YES         YES         YES         YES           R² (WITHIN)         0.2736         0.2715         0.2750         0.2853         0.1398	RECESSION*XCX				-0.0006 0.0005					
MANUF_SHARE         (5.59E-06)         (5.58E-06)         (5.55E-06)         (5.38E-06)         (-2.46E-06)           MANUF_SHARE         -1.2985*         -1.2998*         -1.2935*         -1.2241*         -1.1908*           (0.7270)         (0.7346)         (0.7317)         (0.7180)         (0.6597)           PUBLIC_SHARE         -0.4213         -0.3913         -0.4408         -0.4206         -0.3960           (0.3249)         (0.3180)         (0.3281)         (0.3261)         (0.3386)           N_RCA         0.0003         0.0002         0.0003         0.0003         0.0011           (0.0023)         (0.0023)         (0.0023)         (0.0023)         (0.0023)         (0.0022)           CONSTANT         1.8566***         1.8644***         1.8603***         1.8673***         1.4954***           (0.03567)         (0.3545)         (0.3544)         (0.3505)         (0.2632)           YEAR FE         YES         YES         YES         YES           R² (WITHIN)         0.2736         0.2715         0.2750         0.2853         0.1398					(0.0082)	(0.0065)				
MANUF_SHARE         -1.2985*         -1.2998*         -1.2935*         -1.2241*         -1.1908*           (0.7270)         (0.7346)         (0.7317)         (0.7180)         (0.6597)           PUBLIC_SHARE         -0.4213         -0.3913         -0.4408         -0.4206         -0.3960           (0.3249)         (0.3180)         (0.3281)         (0.3261)         (0.3386)           N_RCA         0.0003         0.0002         0.0003         0.0003         0.0011           (0.0023)         (0.0023)         (0.0023)         (0.0023)         (0.0023)         (0.0022)           CONSTANT         1.8566***         1.8644***         1.8603***         1.8673***         1.4954***           (0.03567)         (0.3545)         (0.3544)         (0.3505)         (0.2632)           YEAR FE         YES         YES         YES         YES           R² (WITHIN)         0.2736         0.2715         0.2750         0.2853         0.1398	<b>EMPLOYMENT</b>	-0.0000*	-0.0000*	-0.0000*	-0.0000*	-2.92E-06				
$\begin{array}{c} - \\ \text{PUBLIC\_SHARE} \\ \text{PUBLIC\_SHARE} \\ \end{array} \begin{array}{c} (0.7270) \\ -0.4213 \\ (0.3249) \\ \end{array} \begin{array}{c} (0.3180) \\ (0.3180) \\ \end{array} \begin{array}{c} (0.3281) \\ (0.3281) \\ \end{array} \begin{array}{c} (0.3261) \\ (0.3261) \\ \end{array} \begin{array}{c} (0.3386) \\ \end{array} \\ \text{N\_RCA} \\ \end{array} \begin{array}{c} (0.0003) \\ (0.0023) \\ \end{array} \begin{array}{c} (0.0023) \\ (0.0023) \\ \end{array} \begin{array}{c} (0.3544) \\ \end{array} \begin{array}{c} (0.3505) \\ \end{array} \begin{array}{c} (0.2632) \\ \end{array} \\ \text{YEAR FE} \\ \text{R}^2 \ (\text{WITHIN}) \\ \end{array} \begin{array}{c} \text{YES} \\ \text{YES} \\ \text{YES} \\ \end{array} \begin{array}{c} \text{YES} \\ \text{O.2750} \\ \end{array} \begin{array}{c} 0.2750 \\ \text{O.2853} \\ \end{array} \begin{array}{c} (0.6597) \\ \text{O.6597} \\ \text{O.6003} \\ $		(5.59E-06)	(5.58E-06)	(5.55E-06)	(5.38E-06)	(-2.46E-06)				
PUBLIC_SHARE         -0.4213         -0.3913         -0.4408         -0.4206         -0.3960           N_RCA         0.0003         0.0002         0.0003         0.0003         0.0011           (0.0023)         (0.0023)         (0.0023)         (0.0023)         (0.0023)         (0.0023)           CONSTANT         1.8566***         1.8644***         1.8603***         1.8673***         1.4954***           (0.03567)         (0.3545)         (0.3544)         (0.3505)         (0.2632)           YEAR FE         YES         YES         YES         YES           R² (WITHIN)         0.2736         0.2715         0.2750         0.2853         0.1398	MANUF_SHARE	-1.2985*	-1.2998*	-1.2935*	-1.2241*	-1.1908*				
(0.3249) (0.3180) (0.3281) (0.3261) (0.3386)  N_RCA		(0.7270)	(0.7346)	(0.7317)	(0.7180)	(0.6597)				
N_RCA         0.0003         0.0002         0.0003         0.0003         0.0011           (0.0023)         (0.0023)         (0.0023)         (0.0023)         (0.0023)           CONSTANT         1.8566***         1.8644***         1.8603***         1.8673***         1.4954***           (0.03567)         (0.3545)         (0.3544)         (0.3505)         (0.2632)           YEAR FE         YES         YES         YES         YES           R² (WITHIN)         0.2736         0.2715         0.2750         0.2853         0.1398	PUBLIC_SHARE	-0.4213	-0.3913	-0.4408	-0.4206	-0.3960				
CONSTANT (0.0023) (0.0023) (0.0023) (0.0023) (0.0022)  1.8566*** 1.8644*** 1.8603*** 1.8673*** 1.4954*** (0.03567) (0.3545) (0.3544) (0.3505) (0.2632)  YEAR FE YES YES YES YES YES  R² (WITHIN) 0.2736 0.2715 0.2750 0.2853 0.1398		(0.3249)	(0.3180)	(0.3281)	(0.3261)	(0.3386)				
CONSTANT 1.8566*** 1.8644*** 1.8603*** 1.8673*** 1.4954*** (0.03567) (0.3545) (0.3544) (0.3505) (0.2632) YEAR FE YES YES YES YES YES R² (WITHIN) 0.2736 0.2715 0.2750 0.2853 0.1398	N_RCA	0.0003	0.0002	0.0003	0.0003	0.0011				
(0.03567)     (0.3545)     (0.3544)     (0.3505)     (0.2632)       YEAR FE     YES     YES     YES     YES       R² (WITHIN)     0.2736     0.2715     0.2750     0.2853     0.1398		(0.0023)	(0.0023)	(0.0023)	(0.0023)	(0.0022)				
YEAR FE         YES         YES         YES         YES         YES           R² (WITHIN)         0.2736         0.2715         0.2750         0.2853         0.1398	CONSTANT	1.8566***	1.8644***	1.8603***	1.8673***	1.4954***				
R <sup>2</sup> (WITHIN) 0.2736 0.2715 0.2750 0.2853 0.1398		(0.03567)	(0.3545)	(0.3544)	(0.3505)	(0.2632)				
	YEAR FE	YES	YES	YES	YES	YES				
# OBS 690 690 690 720	R <sup>2</sup> (WITHIN)	0.2736	0.2715	0.2750	0.2853	0.1398				
	# OBS	690	690	690	690	720				

Notes: Coefficients and standard errors (in parenthesis) reported. Significance levels are posted as p < 0.10, \*\* p < 0.05, \*\*\* p < 0.01. All models incorporate robust standard errors. Models 1-4 are run without the three metropolitan regions of Stockholm, Goteborg and Malmo. Model 5 includes all labour markets.

A much more interesting sets of findings appears when we separate the influence of occupational entry and exit on employment growth across periods of economic expansion and recession (Models 4 and 5). These results are generated by interacting entry and exit variables with the recession dummy. Thus, as the recession dummy assumes the value 0, indicating the period of normal economic activity prior to 2008, the entry and exit variables report the impact on employment growth of changes in the relatedness and complexity of the occupational mix of labour market areas. As the recession dummy assumes the value 1, then the interaction variables for entry and exit indicate how shifts in occupational structure drive employment growth in a period of recession relative to their impact in the period of expansion. Model 4 reveals that in the period of normal growth (before 2008), exiting occupations that are more (less) related to the regional core and entering into more (less) complex occupations

significantly lower (raise) employment growth. This finding suggests experimentation with more complex occupations in times of economic expansion will not likely improve short-run regional fortunes. A plausible mechanism could be local matching deficiencies as new complex specializations may be peripheral to existing core capabilities. Turning to the interaction effects in Model 4, the results show that the negative effects of occupational change just discussed are mitigated by the recession. Thus, for the years after 2008, the relationship between exit from related occupations and regional employment growth is positive and significant. Similarly, the relationship between entry into more complex occupations and employment growth is positive and significant. Periods of economic slowdown thus appear to provide opportunities for occupational restructuring that do not damage short-run employment growth. Crises appear to be periods when experimentation with new occupational possibilities does little marginal damage to the economy. Clearly, more work is required to identify longer-run impacts of such experimentation at the level of the economy as a whole, and for different groups of workers and firms. Adding the three metropolitan regions in Model 5 generates results that are more or less in line with those in Model 4.

Robustness checks involving the use of additional covariates yielded no broad changes to our findings, but did raise some problems of collinearity. Concerns with using annual data led to some experimentation with multi-year periods of change and use of 3-year running means of all right-hand side variables. These experiments caused some variation in the relative magnitudes of core variables, but no appreciable change to the general story outlined above. It is clear from the data that the recession did not influence all regions and sectors evenly. Separating regions into those most and least impacted by the recession does shape the relationship between relatedness, complexity and employment growth, but not in ways that are easily summarized.

#### **Concluding remarks**

One of the main objectives of this paper was to contribute to the growing literature on relatedness and complexity by redressing a somewhat neglected perspective based on microprocesses via occupational data and labour mobility (Whittle and Kogler, 2019). Our approach is different from existing output-based studies that primarily focus on the determinants of new technological specializations (e.g., Balland et al., 2019; Kogler et al., 2017) and also previous studies relying on occupational data at the regional level (e.g., Munerpeerakuul et al., 2013; Farinha et al., 2019). The main difference is that we define related occupations based on the history of worker flows rather than through patterns of occupational co-location. We argue that this approach is advantageous in that it specifies more clearly what the occupational relatedness measure is really capturing. Additional work is needed to explore the correlation between different relatedness measures.

The link between shifts in the occupational mix of regions and spatial uneven development has deep roots within economic geography (c.f., Massey, 1984; Thompson and Thompson, 1985; Markusen, 2004). We engaged this broader concern using longitudinal matched employer-employee data covering Swedish functional labour markets. The core substantive question was to understand how changes in the relatedness and complexity of occupations characterizing

Swedish labour markets impacted short-run changes in the rate of growth of employment. A secondary issue was exploring how these impacts vary across periods of normal economic activity and periods of recession. Knowledge spaces visualize how the structure of occupations varies across Swedish regions of different size and character. We also report values of occupational complexity for Swedish labour-market areas and how these have changed over time.

Our main findings show that the occupation-mix of regions changes at a slower pace than the regional industry-mix, implying that there is more inertia over time in terms of what tasks workers actually perform relative to the products and services they provide. The spatial division of skills does change more rapidly outside metropolitan regions than within them though. Labour-markets are mapped in "smart specialization spaces" (Balland et al., 2019) that highlight how entry and exit increase or decrease the relatedness and complexity of the occupations in which they specialize.

Our results show that changes in the relatedness and complexity of regional occupational structures do impact the rate of growth of employment over the short-run and that these impacts vary markedly over the economic cycle. In times of growth, we find that abandoning occupations close to a region's core capabilities slows employment growth, as does entry into more complex occupations. However, these negative impacts on the rate of growth of employment are nullified in recessions. The old adage, "never waste a good crisis" comes to mind.

In conclusion, the findings presented here provide unpreceded insights into the micro-processes underlying regional branching and whether this translates to employment growth. Our results have a direct connection to the smart specialization literature, in particular the operationalization of that concept by Balland et al. (2019) and Rigby et al. (2019) as they combine relatedness with complexity in a regional setting. While the concept of smart specialization have gained increasing importance in policy and research, it however lacks a solid empirical base (Morgan, 2015), and there may be valid questions of its relevance for peripheral regions (McCann and Ortega-Argiles 2015). Our findings presented here indeed shows that the concepts of economic relatedness and complexity have relevance not only for technological diversification, but also in terms of understanding variations in regional employment growth. This is an important extension given the note of Whittle and Kogler (2019) that the few empirical studies of regional branching, relatedness and complexity have tended to focus on technological knowledge (patents). Here we add to the emerging series of papers that establish the relevance of these concepts across different domains of regional economic activity. Yet, even in the narrow range of papers that explore the importance of relatedness and complexity across labour-markets, the findings are somewhat varied. For example, Davies and Maré (2019) find no association between employment growth and relatedness in New Zealand cities, while Farinha et al. (2019) show that relatedness is key to US urban job growth. Clearly, as the labour market is embedded in different institutional arrangements at national and supranational (e.g., EU) level, much work remains to understand exactly how relatedness shapes labour market dynamics.

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### Appendix

Table A1: The five most complex occupations and the occupations they are most related to

Rank	Occupation	Most related	Second most related	Third most related
1	Writers and creative or performing artists	Artistic, entertainment and sports associate professionals	Optical and electronic equipment operators	Craft printing and related trades workers
2	Business professionals	Administrative associate professionals	Numerical clerks	Finance and sales associate professionals
3	Computing professionals	Computer associate professionals	Architects, engineers and related professionals	Business professionals
4	Other specialist managers	Business professionals	Computing professionals	Finance and sales associate professionals
5	Legal professionals	Public service administrative professionals	Library and filing clerks	Customs, tax and related government associate professionals

Table A2: The five least complex occupations (rank=1 is the least complex of all) and the occupations they are most related to

Rank	Occupation	Most related	Second most related	Third most related
1	Metal- and mineral-products machine operators	Other machine operators and assemblers	Assemblers	Chemical-products machine operators
2	Blacksmiths, tool-makers and related trades workers	Metal- and mineral-products machine operators	Metal-processing-plant operators	Precision workers in metal and related materials
3	Market gardeners and crop growers	Agricultural, fishery and related labourers	Crop and animal producers	Animal producers and related workers
4	Electrical and electronic equipment mechanics and fitters	Precision workers in metal and related materials	Assemblers	Other machine operators and assemblers
5	Crop and animal producers	Forestry and related workers	Fishery workers, hunters and trappers	Agricultural and other mobile- plant operators

Table A3: Pooled descriptive statistics of continuous independent variables and pair-wise correlations.

	Variable		Mean	Min	Max	1	2	3	4	5	6	7
11	ENTRY RLTDN	Entry relatedness density (normalized)	0.02	-2.34	4.16	1.00						
2	EXIT RLTDN	Exit relatedness density (normalised)	-0.02	-3.54	2.55	0.05	1.00					
3	ENTRY COMPLEX	Entry complexity (normalized)	-0.03	-3.00	4.25	-0.42	-0.04	1.00				
4	EXIT COMPLEX	Exit complexity (normalized)	0.01	-4.62	3.92	0.06	-0.22	0.20	1.00			
5	EMPLOYMENT	Regional employment (000s)	60.44	1.04	1327.9	-0.07	-0.06	0.29	-0.38	1.00		
6	MANUF_SHARE	Share of employment in manufacturing	0.20	0.01	0.47	0.03	-0.04	0.06	-0.05	-0.12	1.00	
7	PUBLIC_SHARE	Share of employment in public sector	0.05	0.01	0.19	-0.02	-0.02	0.01	0.04	-0.01	-0.47	1.00
8	N_RCA	Number of occupations with RCA>1.0	41.24	23	63	-0.00	-0.01	0.02	0.06	0.02	-0.38	0.29

*Notes:* All variables are measured by year for each region. The relatedness and complexity variables report whether entry and exit in occupational specializations between years increase or decrease the average relatedness and complexity value of occupations in each region. For the study period as a whole, these values can be read for each region from Figure 5.