

Why bother about region-specific growth patterns and how to identify them?

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Keywords: Regional growth; regional development; evolutionary economic geography; path-dependency; embeddedness; outliers

JEL: O18; R10

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Understanding the causes of regional growth has been of key concern for policy makers and scholars in economic geography and regional science. Regional growth models estimate the effect of various regional factors on the growth of an average region. However, these models leave a large share of regional growth unexplained. This is to be expected, as the embeddedness of regions at various spatial scales from the local to the global invariably leads to growth that is highly region-specific. However, existing quantitative approaches to regional growth are not able to cope with this, treating outliers in growth models as stochastic noise rather than as cases of empirical interest. The paper proposes a method to carve out the region-specific growth component in regional growth models and illustrates this empirically using data for Sweden from 1990-2016. We find robust patterns of periodic region-specific growth outweighing the effect of generic structural factors. This has important implications for how we should think about and empirically address regional growth.

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“Explaining the growth and change of regions and cities is one of the great challenges for social science. Cities or regions, like any other geographical scale of the economic system, have complex economic development processes that are shaped by an almost infinite range of forces. There is a thorny question as to what social science should aim to do in the face of such complexity.” (Storper, 2011, p. 333)

1 Introduction

In this paper, we discuss a fundamental challenge related to one particular form of explaining growth and change of regions and cities, namely the explanation of regional growth through a number of structural factors in regional growth models. Regional growth models, based on different theoretical strands, such as evolutionary theory, institutional theory, or new economic geography, test if and to what extent selected variables are associated with regional growth on average. This paper shifts the analysis from smoothening regional growth around means, being instead interested in what is usually treated as “noise” and “random disturbance”, i.e. the residuals that remain unexplained in regional growth regressions. This appears important as these residuals are indeed “[s]tubbornly high – and often growing” (Rodríguez-Pose, 2013, p. 1036), hence the predictive power of these growth models is decreasing.

In particular, we address a fundamental issue of regional growth that surfaces in the introductory quote from Storper (2011). Regions may develop systematic deviations from average growth paths as a result of the interplay between “an almost infinite range of forces”. If one accepts that knowledge bases, networks, institutions, industries, and infrastructure co-evolve in regions in a path-dependent manner, and that the interplay between these many factors leads to emerging qualities where the outcomes cannot be predicted but are still persistent over time, these region-specific growth deviations are to be theoretically expected.

The implications of this line of reasoning are profound due to the conflict with the basic assumption in regional growth models, namely that residuals in growth regressions are randomly distributed. It suggests that non-random distributions of residuals are not only attributable to omitted variable bias and model misspecification but also to emerging qualities of regional growth trajectories that produce periodic region-specific growth deviations.

The first purpose of this article is to highlight the importance of region-specific growth, which current empirical research either has overlooked or considered as “noise”. The second purpose – and important contribution – is to propose a strategy for identifying regions that stand out due to growth deviations from average regional development trajectories by analysing the residuals in regional growth regressions. To the best of our knowledge, there are no empirical

studies of regional growth that pay closer attention to the “unexplained” regression component. A large residual implies that a specific region exhibits unexpectedly high or low growth given its structural preconditions. The third purpose is to illustrate empirically the proposed identification method and to assess the importance of region-specific growth using data on employment growth across Swedish local labour markets in 2000-2016.

In section 2, the paper elaborates on the theoretical arguments for why region-specific growth patterns are not some odd cases but rather to be theoretically expected. In section 3, we outline the methodology for identifying regions which in certain periods perform better or worse than would be expected from their structural preconditions (that is, the methodology for carving out the idiosyncratic regional growth patterns). Section 4 presents an empirical illustration with linked employer-employee data from Sweden. Section 5 concludes the paper.

2 Why should region-specific growth exist?

The regional development literature has identified a number of generic factors, which are important for regional growth, such as infrastructure, human capital endowments, industry structure, institutions and good governance. In addition to these internal factors, regional development is also shaped by external drivers, such as trade flows, foreign direct investments, and migration. While much regional development research has been preoccupied with regularities in the relationship between these variables and growth over a large number of regions, a closer look at some of the main theories underpinning regional development research reveals that deviations from these regularities may be the norm, rather than the exception. This section responds to the question of why region-specific growth exists after the consideration of these generic factors (which are not subject to scrutiny in this paper). We broadly differentiate between regional and extra-regional embeddedness that may cause region-specific growth and carve out the factors driving it.

2.1 Regional embeddedness as a source of region-specific growth patterns

One of the main reasons why economic geography exists as a discipline is the compelling evidence for a spatial differentiation in income, capital accumulation, production and innovation. A starting point is Alfred Marshall’s (1920) seminal piece on the ”Principles of Economics” where he argues for the importance of external economies arising from co-location. Marshall identified local knowledge spillovers, local labour market dynamics, and the development of a specialised supplier base as key mechanisms. It is notable that he identified these mechanisms in relation to industrial specialisations: “When an industry has thus chosen a locality for itself, it is likely to stay there long: so great are the advantages which people following the same skilled trade get from near neighbourhood to one another” (Marshall, 1920, p. 271). This points to the importance of region-specific growth trajectories beyond general structural factors such as economies of scale, transportation costs, and the share of manufacturing in national income, which may explain the emergence of core-periphery patterns

(Krugman, 1991). The arguments for the existence of such trajectories relate to regional particularities of knowledge bases, learning, networks, and institutions.

Knowledge bases vary significantly between places as a consequence of industrial, educational, and research specialisations, combined with the sticky nature of tacit knowledge and localised learning processes. While it is obvious that skills and competences are developed in and drawn to regions in response to existing specialisations, it took Polanyi (1958) to clearly express why this knowledge remains sticky. He argued that important parts of knowledge are embodied, impossible to codify, and therefore hard to transfer over distance. This type of knowledge is acquired through interaction and practice, and laid the ground for the localised learning thesis (Maskell and Malmberg, 1999). Accordingly, interactive learning is powered through social networks at the local scale (Breschi and Lissoni, 2009, Grillitsch and Rekers, 2015, Kemeny et al., 2016) as well as shared institutions (Gertler, 1995).

Institutions can be both (general) structural and region-specific growth factors. As a structural factor, institutions are relevant for national competitiveness and innovativeness (Nelson, 1993, Hall and Soskice, 2001, Vitols, 2001) and frame the emergence of regional innovation systems (Asheim and Coenen, 2005, Asheim and Gertler, 2005). However, due to interdependencies between a whole set of institutions and region-specific configurations (Gertler, 2010, Grillitsch, 2015) institutions are also a possible reason for region-specific growth patterns. Regional policy mixes and rationales, regional investments in systems of vocational training, R&D, and innovation and technology transfer have been found to explain the competitiveness and innovativeness of regions (Cooke and Morgan, 1994, Morgan, 2016). Furthermore, regional interactions and social networks facilitate the emergence of informal institutions and conventions (Saxenian, 1994, Storper, 1995, Malecki, 2011) that may underpin region-specific innovative milieus (Camagni, 1991, Maillat, 1998, Crevoisier, 2004).

The emergence of specific knowledge bases, networks, and institutions have been identified as major drivers of regional growth trajectories. This gives rise to path-dependent, irreversible developments: “a region moves along a specific development trajectory that affects (as an incentive and selection structure) the kind of competences that are most developed and reproduced, and how the institutional set-up co-evolves, and influences the way production, learning and innovation take place. Consequently, there exists a wide diversity of regional trajectories [...]” (Boschma, 2004, p. 1008).

Recently, the focus in the literature has shifted to the explanation of new industrial path development in regions (Isaksen and Tripli, 2014). Some general structural features of regions have been identified, such as the degree of specialisation and diversification as well as the degree of regional system differentiation, that are related to the forms of new path development that can take place (Grillitsch and Asheim, 2018, Grillitsch and Tripli, 2018). Structural preconditions shape but don't determine regional path development (Martin and Sunley, 2006). Even though regions have similar preconditions, they may develop differently. The emergence of regional growth paths is not only a product of structural preconditions but also a result of

intended and unintended consequences of the actions and interactions of various actors and actor groups (Garud and Karnøe, 2003, Simmie, 2012, Dawley, 2014, Grillitsch and Sotarauta, 2019).

2.2 Extra-regional embeddedness as a source of region-specific growth patterns

While the literature using regional growth models has tended to emphasise factors within a region, there is an increasing understanding of how extra-regional factors shape regional growth. Regions are fundamentally open systems subject to inflows and outflows of people and firms. They rely on connections to other regions to bring new knowledge into the system (Bathelt et al., 2004, Fitjar and Rodríguez-Pose, 2011, Grillitsch and Nilsson, 2015). Migrants bring human capital, as well as different perspectives and international personal and professional networks, which allow regions to access diverse knowledge (Williams et al., 2004, Saxenian, 2007, Faggian and McCann, 2009, Kemeny, 2017, Solheim and Fitjar, 2018). Multinational enterprises (MNEs) bring investments and competence, and their location decisions can have fundamental implications for regional development (Dunning, 1998, Phelps and Fuller, 2000, Cantwell and Iammarino, 2003). There have been warnings that reliance on MNEs may turn regions into branch plant economies that struggle to create sustainable competitive advantage (Cumbers, 2000). However, MNEs may also play crucial roles in upgrading regional industries, depending on their strategies (Mudambi and Santangelo, 2015) and on the extent to which local firms can benefit from knowledge spillovers (Crescenzi et al., 2015).

Perspectives on global cities and the world city network (Beaverstock et al., 2000, Taylor, 2001) note that these external connections create networks of regions. The region's position within this network is a key determinant of regional growth. Hence, the accessibility to and/or the number of external connections of the region may not fully account for its potential to access knowledge from outside. It also matters which other regions it can connect to, and how they in turn are connected to other regions. As each region has a unique position in this network, it is in effect an idiosyncratic factor.

Furthermore, these networks have varying structures across different industries. In the context of globalisation, production of goods and services is increasingly characterised by an international division of labour. Companies in different regions and countries perform different functions, creating global value chains. Depending on the products in question, these are governed in different ways, with implications for coordination across companies and the distribution of power (Humphrey and Schmitz, 2002, Gereffi et al., 2005). Within these value chains, multinational enterprises have established global production networks, with subsidiaries and independent local suppliers performing different functions in the production process. These hierarchical networks distribute knowledge and power between headquarters and local suppliers, and are to a varying extent territorially embedded (Ernst and Kim, 2002, Henderson et al., 2002). In many cases, regional growth is a consequence of regional industries upgrading their positions within these global value chains, i.e. moving from lower to higher-value activities within the value chains (Giuliani et al., 2005, Gereffi, 2014). The opportunities for

upgrading of regional industries are shaped by the value chains which they are in and by their current positions, hence following evolutionary paths (Pietrobelli and Rabellotti, 2011, MacKinnon, 2012).

The global value chains and production networks are themselves related to industries that are subject to different life cycles (Audretsch and Feldman, 1996, Klepper, 1997). When a new industry emerges, the windows of locational opportunity are relatively open, as new institutional structures are needed. This allows regions that succeed in attracting these industries to shift their positions radically (Storper and Walker, 1989, Boschma, 1997). Over time, the industry consolidates and it becomes much more difficult for new regions to develop competitive advantage. In the more mature phase, the potential for innovation declines, competition becomes more cost-based and production becomes more dispersed (Audretsch and Feldman, 1996).

In sum, this suggests that regional growth is fundamentally shaped by regions' unique positions within the global value chains and production networks of industries. As these industries follow different life cycles, these positions furthermore vary across time. Within these systems, the sometimes idiosyncratic location decisions made by multinational enterprises and by individual entrepreneurs can make the difference between growth and stagnation in regions which *prima facie* have relatively similar structural preconditions.

2.3 On the phenomenon of region-specific growth patterns

Because of the above, we expect periodical deviations in the actual growth of regions with similar structural preconditions. Partly, these deviations will be due to measurement errors and omitted variables. Partly, however, they will also be due to the interplay of a multitude of regional and extra-regional factors, which causes unique regional environments.

Some parts of the literature assume a pervasive and long-term influence of such regional environments on growth. For instance, regional entrepreneurship culture is persistent over time and should therefore have a lasting effect on the economy (Fritsch and Wyrwich, 2014). As the factors causing irreversibility and path-dependency in regional systems change slowly by definition (e.g. skills, organisational routines, and institutions), one could expect that these may have a pervasive effect on regional growth in the long-term. However, even if some features of regional systems are changing slowly, the effects of such slow-changing features on regional growth depend on context conditions, e.g. on the extra-regional embeddedness of regions. For instance, technological competencies about combustion engines have been crucial in the automotive industry. These competencies are losing value and may even become negative due to cognitive lock-ins during the transition to electric cars. This coupling of regional and extra-regional dynamics suggests that time and space anchor region-specific growth. In other words, some regions will outperform or underperform their peers in certain periods.

This anchoring in time and space is also caused by micro-level, agentic processes. Strategies, actions and interactions of individuals or groups of individuals will differ even between regions with similar structural preconditions, which has to do with uncertainties about intended and

unintended consequences and thereby variances in perceptions of opportunities and expectations (Steen, 2016, Grillitsch and Sotarauta, 2018). The intended and unintended consequences of actions will feed into, reproduce, or change the regional and extra-regional embeddedness of economic actions. In that way, regions change and absorb those actions in the structural preconditions that once gave rise to unexpected growth.

3 How can we identify region-specific growth?

As mentioned above, it is conventional in the growth modelling tradition based on regional economics to smooth regional growth around means and trends in means and to consider that the cases far off the means are there because of ‘random effects’ or ‘noise’ (Storper, 2011). For economic geographers, however, these unobserved specificities represent the complex, region-specific development processes that should be taken into serious consideration and, if possible, theorised. Following this track of thought, we believe that more attention should be paid to deviations from the means – that is, the residuals in growth regressions – as a tool for identifying idiosyncratic regional growth processes. In what follows, we underline (in general terms) a methodology which allows detecting regions that over certain periods of time deviate systematically from a growth trajectory predicted for them given their structural preconditions.

3.1 Defining structural preconditions

The first task in such an exercise should be to define structural preconditions that affect regional growth across a large panel of regions. As it is not the purpose of this paper to discuss the exact variables representing the structural preconditions, we provide a short summary of the literature on the structural features of regional economies that shape their economic performance. This literature identifies two sets of structural preconditions as the most prominent in developed countries, namely: (1) regional agglomeration and industry mix factors and (2) regional competitiveness factors (Crescenzi et al., 2016, Giannakis and Bruggeman, 2017, Iammarino et al., 2018).

The regional industry mix is the outcome of interactions between supply and demand factors, comparative advantage and specialisation patterns (Groot et al., 2011). From a theoretical perspective, the diversity of the regional economy in terms of sectorial specialisations and typologies of economic activities is an important factor of regional interaction with the overall macroeconomic situation (Crescenzi et al., 2016). For instance, different sectors exhibit different degrees of sensitivity to macroeconomic shocks, which would imply that a more diversified regional employment structure reduces the regional sensitivity to business cycles. Also, a more diverse industry mix is a source of new combinations à la Schumpeter, which create a favourable atmosphere for innovation and productivity improvements (Jacobs, 1969). On the other hand, the beneficial effects of diversity can be counteracted by sectorial interconnections that increase the transmission of shocks from one sector to others (Martin, 2012).

Another important aspect connecting regional agglomeration forces to the growth performance of regions relates to a source of knowledge spillovers in the regional industry mix. The seminal study by Glaeser et al. (1992) gave rise to a lively debate – commonly referred to in the literature as ‘MAR vs. Jacobs’ – on the impact of specialisation and diversification in regional industrial structures on economic growth. MAR refers to theories of Marshall, Arrow, and Romer, who suggested that knowledge spillovers take place predominantly between similar economic activities and give rise to localisation economies. In contrast, Jacobs (1969) claimed that industrial diversity enhances a cross-fertilisation of ideas emanating from different sectoral backgrounds. In this perspective, new knowledge generation is a recombinant process that builds on a pre-existing variety of knowledge that is combined in new ways. A more recent stand on this issue is that a diversity in cognitively similar industries (related variety) is the strongest stimulant of regional growth as such diversity is the most fertile soil for inter-industry knowledge spillovers (Frenken et al., 2007).

All in all, regional agglomeration and industry mix factors play their role in both knowledge generation processes at the regional level and in mediating the performance of the region in various situations imposed by the macro-economic structures in which the region is embedded.

A second subset of structural factors relates to the determinants of regional competitiveness; primarily human capital and innovation efforts. The accumulation of human capital and the allocation of resources to R&D activities are long-term structural characteristics of the regional economy that adjust slowly over time and shape local growth trajectories. For instance, both regional human capital and innovation efforts are crucially linked with the capability of the local economy to generate new knowledge and to receive and exploit ideas, innovations, technologies, and market changes from the outside world (Faggian and McCann, 2009, Crescenzi and Rodríguez-Pose, 2011, Gennaioli et al., 2013). The absorption and generation of new knowledge and its translation into new products and processes are key drivers of regional economic performance. At the same time, the innovativeness and human capital intensity of the regional economy also facilitate regional connectivity with the national and global economy. Regions investing more in both innovation and human capital attract the most sophisticated functions of multinational firms, enabling the regional economy to enter the most advanced stages of global value chains (Crescenzi et al., 2014).

Regional human capital and innovation efforts, apart from the direct impact on the regional economic performance, can simultaneously capture the internal capabilities to innovatively respond to extra-regional developments and the regional embeddedness into more valuable external networks.

3.2 From structural preconditions to growth regression

Having identified the set of structural preconditions that are expected to have an impact on regional growth, the next step is to develop an empirical model that quantifies the impact of those factors in order to estimate the predicted growth of each region. It is important to note that the primary goal of our empirical exercise does not lie in the domain of causal analysis.

Rather, we aim at arriving at the best possible prediction of regional growth based on the information in structural precondition variables and identify the remaining unexplained growth component. The overall task of identifying region-specific growth can then be translated into the task of detecting regions that are periodical outliers in regional growth regressions after accounting for their structural preconditions.

Assume that we observe a set of regions $\mathbf{REG}^n = \{\text{reg}_1, \text{reg}_2, \dots, \text{reg}_n\}$ over a time period $\mathbf{T}^m = \{\text{year}_1, \text{year}_2, \dots, \text{year}_m\}$. Provided that we have data on regional growth and structural preconditions, we can define the following growth model:

$$\Delta Y_{rt}^{t+k} = \beta_0 + \text{INDMIX}_{rt} \beta_1 + \text{COMPET}_{rt} \beta_2 + \delta_r + \theta_t + \varepsilon_{rt} \quad (1)$$

where ΔY_{rt}^{t+k} is the percentage change in the level of growth in region r ($r \in \mathbf{REG}^n$) over k years between t and $t+k$ ($t \in \mathbf{T}^{m-k}$)¹. INDMIX_{rt} and COMPET_{rt} capture the matrices containing variables related to industry mix factors and competitiveness factors, respectively². Apart from the variables, which specify the structural preconditions in regions, we include region-invariant unobserved time effects (θ_t). These exclude the impact of time-specific effects, which are uniform across all regions in the set \mathbf{REG}^n and capture the average effect of national and global economic shocks.

Idiosyncratic regional growth factors are captured by two parameters in the model: First, the regional fixed effects (δ_r) reflect time-invariant or long-term unobservable regional characteristics. These remain constant over the time period \mathbf{T}^{m-k} . Second, ε_{rt} reflects time-specific regional growth idiosyncrasies, i.e. individual years when the region grows more or less than expected.

A k -year period panel model (measuring growth over a period of k years) is preferred over an exploitation of the full (year-by-year) panel structure of the data because the structural preconditions of the regions change rather slowly over time, implying a relatively low year-by-year variance within regions (Firgo and Mayerhofer, 2017). Furthermore, a year-by-year panel only identifies the effects of changes in industrial composition on the regional growth in the following year, leaving out longer-run effects. Given that changes in structural conditions will take time to translate into regional growth, this motivates using the k -year period rather than year-by-year panel structure.

3.3 From growth regression to region-specific growth

After estimating the growth regression specified in (1), we obtain the values of the estimated parameters $\hat{\beta}_i$, $\hat{\delta}_r$, and $\hat{\theta}_t$. Using those, we can derive the point estimates for the level of growth

¹ In that respect, the model uses the ‘rolling’ estimation periods where each subsequent period is moved one year forward. For instance, the period $(t, t+k)$ is followed by the period $(t+1, t+k+1)$. The total number of periods is then $m-k$ and depends on the length of the period k chosen for estimation procedure.

² All variables in INDMIX_{rt} and COMPET_{rt} consist of the values for the first year (t) in each period to mitigate endogeneity concerns.

and, subsequently, the error of predictions e_{rt} . More specifically, we obtain the $n \times m-k$ matrix of the errors of estimation:

$$\mathbf{E}_n^{m-k} = \begin{pmatrix} e_{11} & e_{12} & \dots & e_{1m-k} \\ e_{21} & e_{22} & \dots & e_{2m-k} \\ \vdots & & & \\ e_{n1} & e_{n2} & \dots & e_{nm-k} \end{pmatrix} \quad (2)$$

For each of n regions and $m-k$ estimation years, the elements in \mathbf{E}_n^{m-k} represent the unexplained growth component after accounting for the structural preconditions of each region. Here, values of e_{rt} above zero indicate that model (1) underestimates the regional growth performance. In other words, the region performs better than its structural preconditions would suggest. And, vice versa, values of e_{rt} below zero indicate that the region performs worse than its structural preconditions would suggest, as model (1) overestimates the regional growth performance.

Comparing the unexplained growth component across regions, it is possible to identify the outliers – that is, regions that at certain points in time performed substantially better or worse than their structural preconditions would suggest. The problem, however, is that, apart from the unobserved regional characteristics that are time-specific, the unexplained growth component includes some noise. In order to use this variable to identify region-specific growth, it is necessary to establish a procedure for its systematic evaluation.

To do so, we, first, column-standardise the elements of the matrix \mathbf{E}_n^{m-k} . In other words, we calculate the standard deviation of prediction errors for every year (σ_t), and subsequently transform the prediction errors for all regions in respective years according to:

$$z_{rt} = \frac{e_{rt} - \bar{e}_t}{\sigma_t} = \frac{e_{rt}}{\sigma_t} \quad (3)$$

By doing so, we obtain a matrix of standardised prediction errors:

$$\mathbf{Z}_n^{m-k} = \begin{pmatrix} z_{11} & z_{12} & \dots & z_{1m-k} \\ z_{21} & z_{22} & \dots & z_{2m-k} \\ \vdots & & & \\ z_{n1} & z_{n2} & \dots & z_{nm-k} \end{pmatrix} \quad (4)$$

Value z_{rt} measures the distance of each prediction error from zero expressed in the standard deviations of the distribution of prediction errors for each year of observation (for instance, a value of 1 indicates that the error of prediction is exactly one standard deviation from zero). As before, the values above (below) zero indicate that a region in a specific period deviates positively (negatively) from the prediction based on its structural preconditions³. Subsequently, we examine the matrix \mathbf{Z}_n^{m-k} row-by-row (that is, looking at individual regions). Region-specific growth is identified if the standardised prediction error is above (below) 1 for at least

³ Due to the inclusion of regional fixed effects in the model, the mean error of prediction for each region over the observation period is equal to zero.

$k+1$ consequent years, where k is the length of a growth period in regression model (1). In other words, we identify regions that in a number of consecutive years consistently perform much (at least one standard deviation) better or worse than could be expected given the structural preconditions.

4 Empirical illustration: Does region-specific growth exist in Sweden?

Now that we have outlined the method in general terms, we illustrate it by analysing patterns of regional employment growth in Sweden between 1990 and 2016. The data employed in the analysis come primarily from the *Longitudinal Integration Database for Health Insurance and Labour Market Studies* (for more details see Appendix 1).

The spatial unit employed in the paper is a local labour market (LLM), which is an integrated geographical unit within which most interactions between workers seeking jobs and employers seeking labour occur. Thus, LLMs are appropriate spatial units for linking the supply and demand sides of the labour market and explaining regional labour market performance as a function of endogenous regional factors. In practice, the boundaries of LLMs are defined by commuting patterns between municipalities through maximising the self-containment of commuting flows (SCB, 2010). This procedure identifies 90 local labour markets (as of 2000). Referring back to Section 3.2, this means that we observe a set of regions \mathbf{REG}^{90} over a time period $\mathbf{T}^{27} = \{1990, 1992, \dots, 2016\}$.

4.1 Variables

The dependent variable employed in the empirical analysis is regional employment growth, which is calculated as

$$\Delta emp_{rt}^{t+3} = \frac{\ln(emp_{rt+3}) - \ln(emp_{rt})}{3},$$

where emp_{rt} is the employment in region r in year t .

With respect to the independent variables, the first group of structural factors refers to the regional agglomeration and industry mix factors. These factors provide an overall characterisation of the regional economy without any reference to its functional specialisation. Following the literature, we define the following three variables: regional skill relatedness (as a measure of related variety), reversed Hirschman-Herfindahl index (as a measure of absolute diversity in regional employment mix), and Theil index (as a measure of relative regional specialisation). Appendix 2 provides details on how these variables are constructed.

As regards regional agglomeration, an important determinant of innovation is the degree of urbanisation: there is a consensus that the dynamism of large cities makes them motors of economic growth (Fujita et al., 1999, Duranton and Puga, 2001). Urban agglomeration is also considered to lead to greater innovation (Iammarino, 2005) and to lower barriers and costs of knowledge sharing and transmission across individual and firm networks (Storper and

Venables, 2004). We therefore capture the urbanisation externalities by the population density in the respective region.

The second group of regional factors captures the regional innovativeness and competitiveness. We define three variables. The first two represent the shares of regional employment in high-tech manufacturing and knowledge-intensive services⁴. Human capital effects on regional employment dynamics are captured by the share of regional population with higher education (within the group of workers aged 25+). This way of measuring educational attainment is in line with most of the literature on human capital and regional growth.

Finally, we include some general structural characteristics of the local labour markets as structural controls. For instance, it has been claimed that ‘manufacturing and construction industries have been viewed as being more cyclically sensitive than private service industries, and the latter more sensitive than public sector services’ (Martin, 2012). Moreover, public employment protection mechanisms may prevent a contraction in output from translating into a proportional decline in employment in the regions where a larger share of employment is concentrated in the public sector. More stringent employment protection regulations and less flexible labour markets may shelter the regional economy from temporary shocks (Groot et al., 2011). We therefore account for the share of employment in manufacturing and the share of public employment to control for the sensitivity of regional labour markets to the macroeconomic conditions.

We also control for economic convergence by including measures of the median regional wage level and regional absolute employment. The expectation is that employment will, *ceteris paribus*, grow more rapidly (in per cent) in regions with lower economic development (and, thus, lower median wage) levels and in regions with lower absolute employment. Finally, we account for the level of regional competition for workers, which is defined as the number of establishments per worker. One reservation should be made here. Whilst such a measure might plausibly measure competition, it might also reflect mere scale factors (Bishop and Gripaios, 2010).

All independent variables (except for those which are shares) are log-transformed. To reduce endogeneity, they are recorded at the beginning of each sub-period.

4.2 Regression results

The intention of this paper is not to evaluate the impact of structural characteristics on regional employment growth *per se*, but rather to quantify the remaining unexplained variance after accounting for the structural factors. Nonetheless, we provide a brief reflection on the relationship between structural characteristics and employment growth, as a background to the

⁴ We apply the OECD definition of these industries. High-tech manufacturing includes high-technology and medium-high-technology sectors, which corresponds to the following two-digit sectors in NACE Rev. 1.1. (24, 29-34, 35 excluding 35.1), or in NACE Rev. 2.0. (20-21, 26-30). Knowledge-intensive services correspond to the following two-digit sectors in NACE Rev. 1.1. (61, 62, 64-67, 70-74, 80, 85, 92), or in NACE Rev. 2.0. (50-51, 58-66, 69-75, 78, 80, 84-93).

discussion of outliers. To do so, Table 1 presents the results of estimating the regression specified in equation (1) using the variables summarised in Section 4.1.

Table 1

First, when it comes to the degree of specialisation vs. diversification in the regional employment mix, we observe a positive significant effect from related variety, a negative significant effect from specialisation (measured by the Theil index), and an insignificant effect from absolute diversity. This implies that over the observed time-period, it was the regions with sufficiently (but not too much) diversified employment mixes that were most able to generate employment in Sweden.

Second, with respect to regional innovativeness and competitiveness, there is (somewhat surprisingly) no significant relationship between employment growth and the share of knowledge-intensive activities (both manufacturing and services) in the region. Nor does the human capital variable tend to exhibit any significant impact. The only variable that has a significant association with employment growth is the degree of urbanisation (measured as population density), which as expected has a positive sign.

Finally, with respect to the group of ‘structural controls’, we observe a significant convergence effect (negative sign for the regional employment variable), a positive (but weakly significant) effect from the share of manufacturing in the regional employment, and a negative effect of the public employment share in the regional mix.

Overall, the observed co-variation between regional employment growth and structural factors, at least for the significant coefficients, exhibits the expected direction of relationship.

4.3 Region-specific growth

After estimating the regression presented in Table 1, we move on to the analysis of idiosyncratic regional growth patterns. To do so, we, first, obtain the matrix of prediction errors \mathbf{E}_{90}^{24} as in (2) and transform it into the matrix of standardised prediction errors \mathbf{Z}_{90}^{24} , according to (3). As outlined above, we identify region-specific growth if the standardised prediction error is above (below) 1 for at least 4 consecutive years. Table 2 presents all regions that exhibit such systematic deviations from the average growth prediction according to this definition, while Appendix 4 presents information about all 90 regions in Sweden.

Table 2

Following this methodology, we identified 21 regions that at some point between 1990 and 2016 exhibited a systematic deviation for at least 4 years in a row. Of these:

- seven regions (Arvidsjaur, Gällivare, Kiruna, Laxå, Pajala, Säffle, and Vansbro) had periods during which they grew both above and below what would be predicted by their structural preconditions;
- six regions (Bengtsfors, Emmaboda, Gislaved, Hofors, Sorsele, and Stockholm) exhibited only the positive outlier features; and,
- eight regions (Eskilstuna, Haparanda, Hultsfred, Jokkmokk, Olofström, Strömstad, Söderhamn, and Ånge) had periods of growth below the prediction by the structural factors.

Looking at temporal and regional patterns, we also derive a series of further stylised facts:

1. Outlier regions represent a broad range of size groups – from the metropolitan local labour market of Stockholm on the right side of the distribution (with a population of 2.8 million inhabitants in 2018) to the local labour market of Sorsele on the left side (with a population of 2522 inhabitants in 2018). In that respect, the methodology is not biased towards any particular group of regions with respect to their size;
2. There is no clear temporal correlation in the outlier patterns. That is, we observe both negative and positive outlier tendencies throughout the whole observation period. This implies that the proposed methodology tends to do a good job in distinguishing the region-specific growth from the national growth pattern.

Another way to look at the residuals is to compare them with the observed employment growth simultaneously (see Figure 1). One would expect positive outliers to be regions with exceptionally fast growth, while negative outliers would be regions with exceptionally slow growth in the respective period. The latter is, in general, true: there appears to be a strong correlation between the value of the standardised residual and the actual growth (lower left quadrant in Figure 1).

However, when it comes to positive outliers, the situation is more interesting. On the one hand, we have a bunch of regions that demonstrated positive employment growth, while being positive outliers (upper right quadrant in Figure 1). However, the growth tempo is not correlated with the size of the standardised residual. On the other hand, there is a group of regions which are *lucky losers* (lower right quadrant in Figure 1), which demonstrate a low growth performance, and yet they are still positive outliers, implying that they shrank more slowly than their structural preconditions would suggest.

Figure 1

The above thus illustrates clear patterns where some regions over a period of at least 4 years consistently perform better or worse than could be expected considering their structural preconditions. We have also investigated the usefulness of the regional fixed effect for capturing regions that over the whole period perform better or worse than an average region. The regional fixed effect, which in effect is a dummy variable for each region, takes into consideration unobserved and time-constant factors influencing regional growth. For instance, this could relate to institutional factors such as an entrepreneurial culture, which by definition changes very slowly.

However, it turns out that the size (and even sign) of the estimated fixed effects is extremely volatile to which structural variables are included in the model. Hence, it holds that “[t]he sense in which the a_i [regional fixed effect] can be estimated is generally weak. [...] The reason is that, as we add each additional cross-sectional observation, we add a new a_i . No information accumulates on each a_i when T [number of time periods] is fixed. With larger T , we can get better estimates of the a_i , but most panel data sets are of the large N [number of regions] and small T variety” (Wooldridge, 2002, p. 446). In our case, we have 90 regions, thus 90 regional fixed effects and observations for 24 time periods. This contains insufficient information to produce reliable estimates for the regional fixed effect. In most empirical situations aiming at estimating regional growth, the situation will be similar. Thus, the regional fixed effects are not a good choice to define region-specific growth.

Interestingly, this is not the case for the residuals, which are remarkably robust to which explanatory factors are included in the model. This can be investigated by comparing the residuals of the fully specified model with the residuals of models with fewer variables. Using the most extreme case, we illustrate the robustness of the methodology by comparing the residuals of the fully specified model with the ones resulting from a model that only includes year and regional fixed effects. As shown in Table 3, the average differences are relatively small, ranging from 0.0017 for Stockholm to 0.0083 for Strömstad. This also implies that including the battery of time-variant structural variables leads to a rather low improvement of growth predictions for these regions with periods of exceptionally high or low growth.

Table 3

Figure 2 illustrates region-specific growth paths for Stockholm, Gällivare, and Strömstad, which are the regions with the lowest, median, and highest average differences between residuals of the fully specified and the fixed effects only model. The figures show clear patterns of region-specific growth in all cases. For Stockholm, as well as for Gällivare, the two lines representing the residuals in each year of observation for the two models are very close to each other. In other words, the inclusion or exclusion of structural variables does not play a substantial role for these regions.

For Strömstad, the general trend appears similar. However, when inspecting the graph in greater detail, some important differences surface. In this case, the fully specified model results in more negative residuals in the 90s and more positive ones after 2005 than the model with only fixed effects. Such more substantial deviations can be observed in two out of the 21 regions. Overall, therefore, the proposed method for identifying region-specific growth is surprisingly robust to which structural variables we include in the models.

Figure 2

A final remark relates to the importance of the region-specific growth component, which is an unexpected but still important finding of the empirical illustration. Overall, the potential of the structural variables to explain regional growth variation is low and largely concealed in relatively high R^2 values supposed to measure the fit of the model. This has already become apparent by the fact that in most cases the residuals using a full model do not deviate substantially from the residuals of a model that only includes the time and regional fixed effects. Another way of illustrating this is by summing up the squared residuals and comparing different models.

Using as a starting point the total variation in regional growth after considering average yearly growth performance, this means considering that in some years all regions grow on average more than in other years. This total regional variation can be explained by including various factors. First, we include a regional fixed effect (i.e. a dummy variable for each region). The regional fixed effects account for approximately 32% of the regional variation in growth. If we then add all other explanatory factors as shown in Table 1, the total of the structural variables including the regional fixed effects account for only 42% of regional variation. This means that in total 58% of regional variation remains unexplained. While this includes stochastic disturbances as well as more systematic deviations in regional growth, it reflects that region-specific growth is potentially a very important phenomenon.

5 Conclusions

While regional development research has traditionally mainly been preoccupied with identifying regularities explaining growth across regions, this paper turns attention to the outliers in regional growth regressions. From a theoretical perspective, there are many reasons to expect regions to exhibit idiosyncratic growth patterns. Regional development is a function of a complex web of intra- and extra-regional endowments of knowledge, resources and networks, characterised by mutual dependencies and interactions across many factors. Hence, some regions can be expected to outperform their peers over shorter or longer periods, while others lag behind.

The paper proposes a method for identifying these regions. We identify two parameters in regional growth regressions that are relevant for this purpose: First, regional time-specific residuals can be used to identify short-term and medium-term trends. When such residuals are sufficiently large and maintain the same direction over a period of several years, they reflect a region-specific growth component that deviates substantially from the expected average growth performance. The analysis shows that these residuals are not heavily affected by the inclusion or exclusion of other variables in the model. This makes the residuals a valuable tool for identifying shorter-term outlier regions.

Second, regional fixed effects will pick up relatively permanent or long-term differences between regions. It has to be acknowledged, as pointed out by Wooldridge (2002), that the estimations of the regional fixed effects tend to be weak, especially if the period of observation is short. Using 27 years of observations in Sweden, we find that the regional fixed effects change substantially with the inclusion or exclusion of variables in the model. Hence, it is problematic to use fixed effects to identify outlier regions.

Illustrating the results with Swedish register data, we identify regions that exhibit growth deviations in the short- and medium-term. These come in all shapes and sizes, from the capital to tiny peripheral regions. They encompass positive outliers, negative outliers, or regions that are both during the period of observation. Furthermore, outliers are not limited to a certain phase of economic transition but appear throughout the whole study period.

Region-specific growth is not only a clearly identifiable empirical phenomenon; it is surprising how large the share of regional growth variation is that remains unexplained in standard growth regressions. Considering the total regional variation, 58% remains unexplained after considering all structural factors that have received primary attention in the recent literature. Of the 42% of regional variation explained by structural variables, the largest part can be attributed to regional fixed effects.

This has profound implications for quantitative and qualitative research in economic geography. First, the method illustrated here serves as a tool for identifying regions with growth patterns that deviate substantially in certain periods from the expected average performance. It thus points to development trajectories that cannot be well explained by the configuration of structural factors. It points to periods in which combinations of intra-regional and extra-regional embeddedness shape specific and deviating growth trajectories. This method also unveils extreme cases of unexpected growth (or decline), from which substantial new knowledge can be gained through in-depth case studies (Eisenhardt and Graebner, 2007).

Second, the findings pose a challenge for quantitative studies. Changes in structural factors, which are typically considered in growth regressions, explain only a surprisingly small share of regional growth variations. This can simply have to do with omitted time-variant structural variables. Taking this problem seriously, it is necessary to acknowledge that such omitted variables potentially affect estimations in a substantial way.

The problem may, however, be rooted more deeply in the way regional growth is perceived and modelled. If the combination of regional and extra-regional factors constitute opportunities and constraints for growth that are region- and time-specific, and if actors perceive and act upon those in a variegated manner (Grillitsch and Sotarauta, 2019), regional pathways are expected to emerge that have little to do with modelled averages in regional growth regressions. While Boschma (2004, p. 1008) argues theoretically for a “wide diversity of regional trajectories”, it is worrying that the empirical strategy of quantitative papers is largely about estimating averages. This cries for the development of new methods that are both closer to this theoretical understanding and better equipped for reducing the so far unexplained regional growth variations.

Finally, an obvious limitation of this paper is that it does not empirically test the causes of region-specific growth deviations. Theoretically, it discusses a number of reasons why such specific trajectories are expected and empirically, it shows that they exist. Hence, the paper is limited to kindling an interest in the (large) part of regional growth that does not follow standard explanations. We illustrate a method that directs attention to regional trajectories that deviate strongly from the expectations, thereby allowing for a systematic analysis of the factors causing such deviations. The paper also questions standard modelling approaches, hopefully, leading to new insights about key drivers of regional growth.

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Table 1. Employment growth and structural preconditions at the regional level in Sweden, 1990-2016

Dependent variable: Employment growth	
Related variety	0.0366** (0.0173)
Theil index	-0.0095*** (0.0031)
Diversity	-0.0066 (0.0049)
Competition	-0.0078 (0.0111)
Manufacturing share	0.0555* (0.0330)
High-tech manufacturing share	0.0044 (0.0282)
Knowledge-intensive services share	0.0178 (0.0226)
Public employment share	-0.0675** (0.0330)
Median wage	-0.0026 (0.0332)
Human capital	0.0551 (0.0627)
Population density	0.0768*** (0.0273)
Regional employment	-0.1199*** (0.0170)
Constant	0.8172*** (0.2184)
N	2160
Regional fixed effects	Yes
Temporal fixed effects	Yes
R-squared within	0.7541
R-squared between	0.2646

Robust standard errors clustered at the regional level are reported in brackets. ***(**,*) indicate a significant difference from zero at the 1% (5%, 10%) level.

Table 2. Regions exhibiting deviating growth periods, 1990-2016

Local labour market	1990	1991	1992	1993	1994	1995	1996	1997	1998	1999	2000	2001	2002	2003	2004	2005	2006	2007	2008	2009	2010	2011	2012	2013		
	1993	1994	1995	1996	1997	1998	1999	2000	2001	2002	2003	2004	2005	2006	2007	2008	2009	2010	2011	2012	2013	2014	2015	2016		
Arvidsjaur	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-		
Bengtsfors		+	+	+	+																					
Emmaboda			+	+	+	+	+	+																		
Eskilstuna	-	-	-	-																						
Gislaved		+	+	+	+	+	+																			
Gällivare	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	+	+	+	+	+	+	+		
Haparanda	-	-	-	-	-	-																				
Hofors			+	+	+	+	+																			
Hultsfred																										
Jokkmokk							-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	
Kiruna	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	+	+	+	+	+	+	+	+	
Laxå							+	+	+	+												-	-	-	-	
Olofström																										
Pajala																						+	+	+	+	+
Sorsele		+	+	+	+	+	+	+	+	+																
Stockholm											+	+	+	+												
Strömstad	-	-	-	-	-	-	-	-	-	-	+	+	+	+				-	-	-	-					
Säffle			+	+	+	+																				
Söderhamn																										
Vansbro							+	+	+	+								-	-	-	-	-	-	-	-	
Ånge																										

Note:

- negative outlier: implies that a region performed substantially worse in terms of employment growth than would be predicted by its structural preconditions;

+ positive outlier: implies that a region performed substantially better in terms of employment growth than would be predicted by its structural preconditions.

Table 3. Average yearly difference in residuals between the fully specified model and a model only including year and region fixed effects

Local labour market	Average yearly difference
Stockholm	0.0017
Eskilstuna	0.0022
Hofors	0.0025
Gislaved	0.0027
Änge	0.0029
Bengtsfors	0.0034
Säffle	0.0035
Vansbro	0.0036
Kiruna	0.0036
Emmaboda	0.0039
Gällivare	0.0040
Sorsele	0.0041
Haparanda	0.0042
Jokkmokk	0.0047
Pajala	0.0048
Olofström	0.0053
Laxå	0.0057
Hultsfred	0.0058
Arvidsjaur	0.0065
Söderhamn	0.0080
Strömstad	0.0083

Figure 1. Standardised residuals vs. employment growth for outlier regions

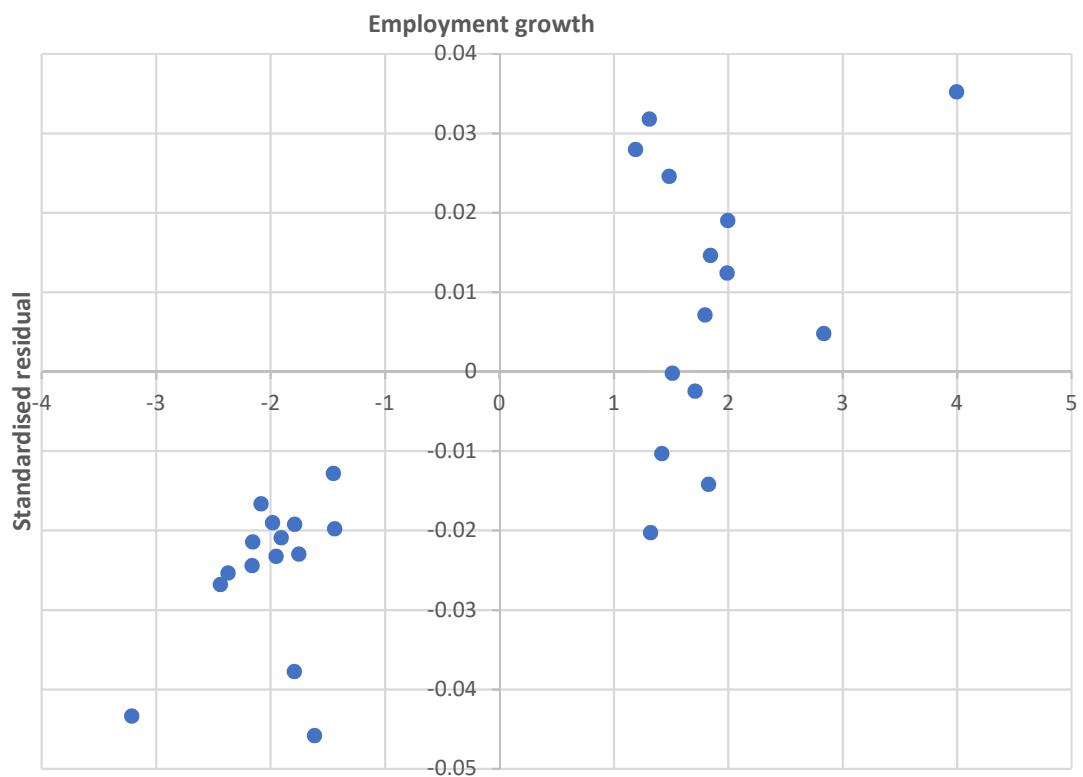
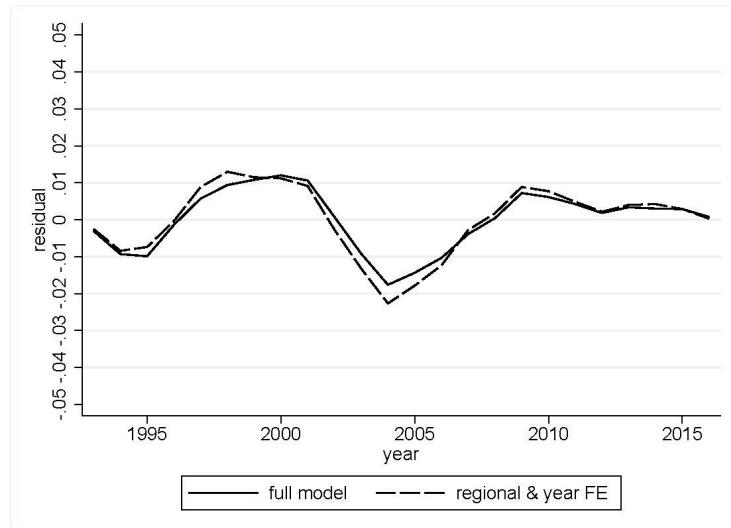
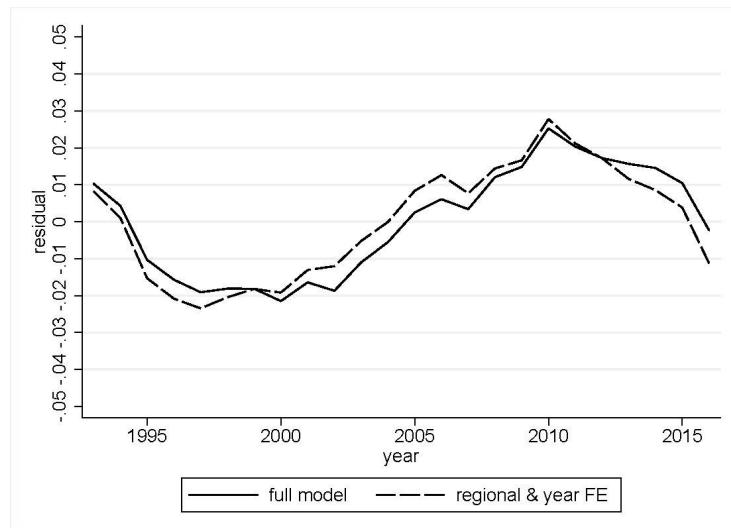


Figure 2. Illustrations of region-specific growth paths

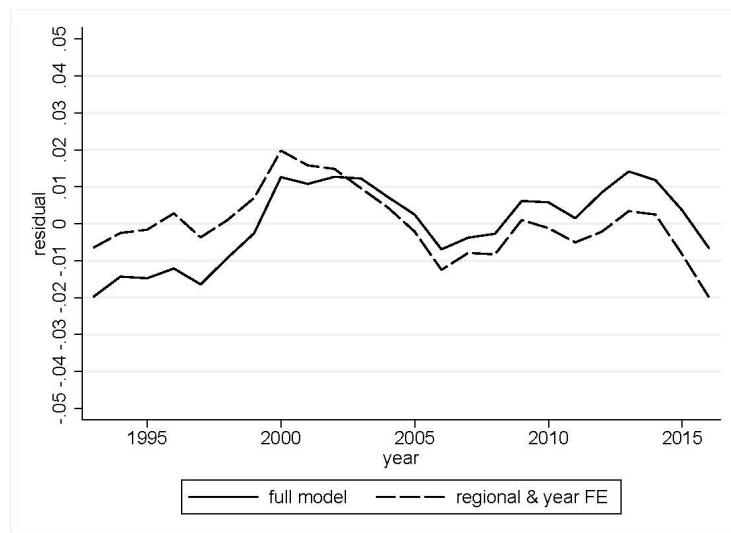
Stockholm



Gällivare



Strömstad



Appendix 1: Data

The *Longitudinal Integration Database for Health Insurance and Labour Market Studies* (LISA) is an anonymised linked employer-employee database that aims at complementing traditional labour market statistics and providing a better description of the labour market and people's relationship to the world of work (SCB, 2016). It is a total-count individual register: all individuals registered in Sweden on December 31 are included in the population for the reference year. LISA is a longitudinal database, meaning that the data for the same person can be linked for all years in which she is included in the population.

LISA integrates the annual data from several registers, including education, income, employment, health insurance, and population registers. The connection of an employee to an employer is denoted by the identity number of the firm and the establishment where she has her main employment. The data also contains detailed information on various individual variables, such as age, education, annual earnings, municipality of residence and employment, industry of employment, etc. Annual data cover the period between 1990 and 2016.

Classification of economic activities is based on the Swedish Standard Industrial Classification (SNI), which is the Swedish implementation of the Statistical Classification of Economic Activities in the European Community (NACE). During the period of observation, three versions of industry classifications are employed in the datasets: SNI1992 (NACE Rev. 1.0), SNI2002 (NACE Rev 1.1), and SNI2007 (NACE Rev 2.0) The structure of these are summarized in Table 1 below.

Table 1. NACE revisions

	NACE Rev. 1.0	NACE Rev. 1.1	NACE Rev 2.0
Sections (1-digit)	17	17	21
Divisions (2-digit)	60	62	88
Groups (3-digit)	223	224	272
Classes (4-digit)	505	514	615
Sub-classes (5-digit)	755	774	821

As SNI2002 is a result of a minor revision of SNI92, it is possible to establish unambiguous links between these two schemes in order to ensure classification consistency over the whole observation period. SNI92 and SNI2002 are merged at the five-digit level and further aggregated into 505 four-digit industries.

When it comes to ensuring the comparability of NACE Rev. 1.1 and NACE Rev 2.0, the direct conversion between the two classification systems does not work very well. As there are more industries in NACE Rev. 2.0, switching between the classification systems in the calculation of certain independent variables may lead to breaks in values of these variables. This might in turn

result in decreasing quality of the estimated model. When describing the individual variables, we discuss how we deal with this issue.

Appendix 2: Construction of industry mix variables

The first step in calculating the degree of related variety at the regional level is defining which industries are related to each other. Following the argument of Kuusk and Martynovich (2018) that in long-term studies, it is reasonable to employ revealed relatedness measures, we define two industries as related to each other if the flow of labour between them is higher than statistically expected (Neffke and Henning, 2013). That is, first, for each pairwise combination of four-digit industries, we calculate the observed national labour flow (F_{ij} , where $i \neq j$). If it is non-zero, we say that there is an observed tie between industries. Second, based on industry sizes, growth, and average wages we estimate an expected labour flow \widehat{F}_{ij} and calculate the ratio of observed to predicted flows:

$$SR_{ij} = \frac{F_{ij}}{\widehat{F}_{ij}}.$$

Here, values larger than 1 (at a 5 per cent significance level) indicate the presence of a relatedness tie between industries. Appendix 3 provides more detailed information on the procedure. As we expect the network of related industries to evolve over time, we iterate this procedure for 24 periods: 1990-1993, 1991-1994, 1992-1995, ..., 2013-2016.

Once 23 matrices of related industries are obtained, we calculate the *regional skill relatedness* indicator as proposed by Fitjar and Timmermans (2017):

$$RSR_{rt} = \frac{(\sum_{i=1}^N \left(\frac{d_{irt}}{2} \right) \sqrt{P_{irt}}) / N_{rt}}{(\sum_{i=1}^N \sqrt{P_{irt}}) / N_{rt}}$$

where RSR_{rt} is the regional skill relatedness in region r in year t ⁵; d_{irt} is the number of incoming and outgoing relatedness ties for each industry i present in a region r (according to the skill relatedness matrix) in year t ; P_{irt} is the share of industry i in the regional employment in year t ; and N_{rt} is the number of industries present in region r in year t . The resulting variable represents the degree of complementarity in the regional employment mix, or, in other words, degree of related variety.

This indicator is calculated for four-digit industries. We can therefore expect that the switch between NACE Rev. 1.1 and NACE Rev. 2.0 will substantially affect the value of the variable. We therefore propose to correct the RSR value according to the following procedure:

⁵ t is a first year in the respective period ($t, t+k$)

1. in years for which both industry classification schemes are available (e.g., in Sweden 2007-2010), we generate national relatedness matrices and calculate RSR for all regions in both NACE Rev. 1.1 and NACE Rev. 2.0;
2. we calculate the correction coefficient

$$RSRcorrcoef_r = \frac{RSR_r^{NACE2}}{RSR_r^{NACE1.1}}$$

This allows us to see how much the measures deviate in each region. For example, it is equal to 1.08 in Stockholm, 0.97 in Markaryd, and 1.08 in Kiruna. For the majority of regions in Sweden, RSR for 2007-2010 calculated in NACE Rev. 2.0 is about 6%-9% higher than the one calculated in NACE Rev. 1.1.

3. we calculate the corrected RSR as

$$RSRcorrected_{rt} = \begin{cases} RSR_{rt} & \text{when it is calculated in NACE Rev. 1.1} \\ RSR_{rt} / RSRcorrcoef_r & \text{when it is calculated in NACE Rev. 2.0} \end{cases}$$

To measure the *absolute diversity* in the regional employment mix, we calculate the reverse Hirschman-Herfindahl index defined in the following way:

$$Diversity_{rt} = \frac{1}{\sum_{i=1}^N q_{irt}^2}$$

where q_{irt} is the employment share of a **two-digit industry** i in region r in year t .

Following van Oort, de Geus, and Dogaru (2015) and Firgo and Mayerhofer (2017), we include the Theil index (the sum of location quotients of the SNI 2-digit industries weighted by their employment shares within a region) as a measure of *relative regional specialization*. It is calculated as:

$$Theil_{rt} = \sum_{i=1}^N \frac{q_{irt}}{q_{it}} * \ln \left(\frac{q_{irt}}{q_{it}} \right)$$

where q_{irt} is the employment share of a **two-digit industry** i in region r in sub-period t ; and q_{it} is the employment share of a two-digit industry i in national employment in sub-period t . While this index has the drawback of not accounting for the absolute size of particular sectors in the region, it has been proven to be a robust estimator of localisation economies.

The difference between the two latter measures is that while the absolute diversity measure reflects the concentration of employment within a region, the Theil index transforms the individual sectoral concentration measures into a generalised between-region specialization measure.

As both the reverse Hirschman-Herfindahl and Theil indices are calculated at the two-digit level, we do not expect much disruption in the values of the variables when the industry classification scheme is switched (as the number of industries at the two-digit level is comparable).

Appendix 3. Estimating relatedness ties between industries⁶

This section describes the procedure for estimating the presence of relatedness ties between four-digit industries. For illustration purposes, we exemplify the procedure for the first sub-period considered (1991-1994).

Data and definitions

The original data contains information on all individuals registered in Sweden for each year between 1991 and 1994. We define an individual as a worker if she (1) is in a working age (16-64) according to the pre-2007 Statistics Sweden definition, (2) has a non-zero income from employment, and (3) is affiliated with an establishment with a registered industry code. Establishments are assigned to four-digit industries according to the classification scheme explained in Section 3 of this paper. Industries that employ fewer than 250 persons on average per year are excluded from the analysis as they are too small to generate or absorb significant labour flows.

Inter-industry labour flows consist of the sum total of individual labour market moves across industries. We register a change in an industry of employment if an employee moves to another establishment at another firm in another industry from one year to the next. By requiring that an employee changes a firm and establishment of employment, we avoid a possible situation when an establishment is reassigned to a different industry.

As discussed in Section 2 of the paper, we can estimate relatedness ties between industries more accurately by limiting the analysis to individuals who are likely to possess industry-specific skills. We therefore disregard all flows involving individuals who earn wages below than the median wage in the respective industry. The main idea here is that firms pay higher wages to employees who possess skills that confer competitive advantage to the firm. Individuals with few skills deemed critical in the industry will earn wages that are low relative to that industry's overall wage level. This does not necessarily imply that individuals with low wages do not have any industry-specific skills. However, this strategy is helpful to reduce the noise in the relatedness estimates.

Estimating relatedness ties between industries

Labour flows between industries depend not only on whether industries are related or not, but also on certain general characteristics of the industries involved. In other words, some industries

⁶ This section of the paper is largely based on NEFFKE, F. & HENNING, M. 2013. Skill relatedness and firm diversification. *Strategic Management Journal*, 34, 297-316..

may exhibit substantial in- and outflows of labour regardless of their relatedness to other industries. Therefore, it is necessary to develop a measure of expected labour flows which would incorporate those additional factors into the analysis. We choose three variables: size of industries, employment growth in industries, and average wages in industries involved in estimation.

Given that labour flows constitute an overdispersed count variable with the majority of observations being zero (there are no labour flows between most industries), it is appropriate to use a zero-inflated negative binomial (ZINB) model. The ZINB regression equation has two components: a regime selection equation and a count data component. The regime selection equation determines whether there will be any flow at all. Next, the count data component estimates the size of the flows, assuming that a nonzero regime is selected.

We pool all data by summing labour flows and employment data across 1991-1994 to raise the efficiency of the estimates. Following (Neffke and Henning, 2013), we estimate a model that uses variables in levels for the regime selection equation and log-transformed variables for the count data equation:

$$E(F_{ij}|v_i, w_j, \varepsilon_{ij}) = [1 - \pi_0(\gamma + \delta_i \text{emp}_{i,1991-1993} + \delta_j \text{emp}_{j,1992-1994})] \cdot \\ f(\alpha + \beta_{1i} \log(\text{emp}_{i,1991-1993}) + \beta_{2i} \log(\text{wage}_{i,1991-1993}) + \beta_{3i} \text{growth}_i + \\ + \beta_{1j} \log(\text{emp}_{j,1992-1994}) + \beta_{2j} \log(\text{wage}_{j,1992-1994}) + \beta_{3j} \text{growth}_j)$$

with i the industry of origin of a flow and j the industry of its destination, π_0 is the probability that a flow can, in principle, take place, $\text{emp}_{k,t}$ is the sum of employment in industry k across years t , $\text{wage}_{k,t}$ is the average wage in industry, and growth_k is the employment growth in industry k across the observed years.

Using the point estimates of the parameters in the equation above, we calculate the expected labour flows (\widehat{F}_{ij}) for all pairwise industry combinations. Comparing those to the observed labour flows (F_{ij}) for the same industry combinations, we obtain the measure of relatedness between industries:

$$SR_{ij} = \frac{F_{ij}}{\widehat{F}_{ij}}$$

Here, values over 1 indicate the presence of an observed relatedness tie between industries.

Determining the significance levels of skill-relatedness estimates

As noted above, there are no labour flows between the vast majority of industries. Importantly, in many such cases, predicted labour flows are negligible as well. What is more, whenever \widehat{F}_{ij} is only a fraction of one, an increase in the labour flow from zero to one individual will lead to large changes in the skill-relatedness index. Thus, skill relatedness is not estimated with equal

precision for all industry combinations. To quantify the precision of our estimates, we construct confidence intervals.

To do so, we assume that all employees in an industry have the option of switching to a new job in a new industry. If N denotes the number of industries present in the national economy, each individual faces N independent choices: one is staying in the current industry, and the other $N-1$ choices represent moves into each of the remaining industries. The choice to switch jobs can now be modelled as a Bernoulli experiment with a probability of success equal to p_{ij} and the resulting aggregate labour flow from i to j , F_{ij} , is the outcome of a binomial experiment $BIN(n, p)$ where n is equal to the employment in industry i and p is equal to p_{ij} :

$$F_{ij} \sim BIN(emp_i, p_{ij}).$$

The question of how informative a specific labour flow is, is now translated into the question of how likely it is to observe F_{ij}^{obs} merely by chance. Let \hat{p}_{ij} be the expected counterpart of p_{ij} :

$$\hat{p}_{ij} = \frac{\hat{F}_{ij}}{emp_i}.$$

If we take \hat{p}_{ij} as a benchmark, the question above corresponds to a statistical test of whether F_{ij}^{obs} is exceptional, assuming that \hat{p}_{ij} represents the real probability that an individual will move from industry i to industry j . If $SR_{ij} > 1$ then the p-value of the corresponding one-sided test can be calculated as follows:

$$P(x \geq F_{ij}^{obs} | p_{ij} = \hat{p}_{ij}) = 1 - \sum_{r=0}^{F_{ij}^{obs}-1} \left[\hat{p}_{ij}^r \cdot (1 - \hat{p}_{ij})^{emp_i-r} \binom{emp_i}{r} \right].$$

Based on a p-value of five percent, between 1991-1994 SR_{ij} is significantly larger than 1 in 6167 industry combinations. Given that 500 industries were present in the Swedish economy during those years and 27549 pairwise industry combinations contained non-zero observed labour flows, relatedness ties correspond to 2.5 per cent of possible ties and 22.4 per cent of observed ties.

Appendix 4: Regional outliers

Local labour market	1990-1993	1991-1994	1992-1995	1993-1996	1994-1997	1995-1998	1996-1999	1997-2000	1998-2001	1999-2002	2000-2003	2001-2004	2002-2005	2003-2006	2004-2007	2005-2008	2006-2009	2007-2010	2008-2011	2009-2012	2010-2013	2011-2014	2012-2015	2013-2016		
Arjeplog							+			-	-	-	-	-	-	-	+	+	+							
Arvidsjaur	-	-	-	-	-	-	-	-	-	-	-	+	+	+	+	+	-	-	-	-	-	-	+	+		
Arvika								-										-	-							
Avesta											+		+													
Bengtsfors	+	+	+	+	+				-	-		-	-	-	-	-		+								
Bollnäs							+										+									
Borås																										
Dorotea	-	-							-			+	+									+			+	
Emmaboda		+	+	+	+	+	+			+	+	+	-	-	-	-										
Eskilstuna	-	-	-	-						+	+						+									
Fagersta									+																+	
Falkenberg								-	-	-																
Falun-Borlänge																										
Filipstad										+	+		-	-								+	+	+	+	
Gislaved		+	+	+	+	+	+	+																		
Gotland	+									+									+							
Gällivare		-	-	-	-	-	-	-	-	-	-						+	+	+	+	+	+	+	+		
Gävle																										
Göteborg	-	-	-						+	+			+													
Hagfors																									+	
Halmstad																										
Haparanda	-	-	-	-	-	-	-										+	+	+	+				+		
Hofors		+	+	+	+	+	-							+												
Hudiksvall																										
Hultsfred		+	+						+			-	-	-	-	-			+	+						
Hällefors	-	-	-	-	-			+		+	+	+														
Härjedalen	+					+			-			-	-	-				+	+							
Härnösand	+	+	-	-	-	-				+	+	+														
Jokkmokk	+	+							-	-	-	-	+	+	+											

Storuman	+	-	-	-	+	-	-	-	-	-	+	+		
Strömstad	-	-	-	-	-	+	+	+	+	+			+	+
Strömsund						-	-	-	-	+	+		+	+
Sundsvall														
Säffle	+	+	+	+	+					+	-	-	-	-
Söderhamn	+	+				+	+	+	-	-	-	-		+
Torsby						-								
Tranås						+		+					-	
Trollhättan	-	-				+	+	+	+				-	-
Umeå														
Vansbro	-		+	+	+	+	+		+		-	-	-	-
Varberg						-	-	-					+	
Vetlanda	-	-									-			
Vilhelmina	+		+		+	-								
Vimmerby	-	-	-				+	+			+			
Värnamo				+	+						-	-		
Västervik												+	+	
Västerås														
Växjö														
Älmhult									-				+	+
Ånge	+	+		+	+	+			+	+			-	-
Årjäng	-	-			+	+			-	+	+	+	-	-
Åsele	+	+	+				+		-	-		+	-	-
Örebro														
Örnsköldsvik														
Östersund														
Överkalix	-	-	-	-		+				+	+	+	+	+
Övertorneå										+	+	+	+	-

Note:

- negative outlier: implies that a region performed substantially worse in terms of employment growth than would be predicted by its structural preconditions;
- + positive outlier: implies that a region performed substantially better in terms of employment growth than would be predicted by its structural preconditions.