Papers in Evolutionary Economic Geography

18.34

What kind of related variety for long-term regional growth?

Kadri Kuusk and Mikhail Martynovich

Utrecht University
Urban & Regional research centre Utrecht

WHAT KIND OF RELATED VARIETY FOR LONG-TERM REGIONAL GROWTH?

Kadri Kuusk
kadri.kuusk@keg.lu.se
Department of Human Geography, Lund University

Mikhail Martynovich
mikhail.martynovich@keg.lu.se
Department of Human Geography, Lund University

Abstract
We investigate the evolution of relatedness linkages between Swedish industries during five sub-periods between 1991 and 2010. Distinguishing between the stable ties (present in all sub-periods) and non-stable ties (emerging, disappearing, etc), we demonstrate that the relatedness linkages change considerably over time. Furthermore, we show that the changes in the relatedness matrix matter for the impact of related variety on regional employment growth. We argue, therefore, that the relatedness linkages have a 'best before date' and that the choice of what relatedness indicator to apply and how deserves more consideration than it is usually given.

Keywords: relatedness, evolution, related variety, regional growth, skill relatedness, Sweden

JEL codes: L16, O33, R11, R12

1. Introduction

In this paper, we investigate the evolution of relatedness linkages between industries over time and its implications for the long-term development of regions. We focus on the relationship between related variety and regional employment growth, using the newly developed regional skill relatedness indicator (Fitjar and Timmermans 2017). Our results demonstrate that the relatedness linkages indeed change considerably over time and that these changes matter for what kind of impact related variety has on regional economic growth. This leads us to argue that due to the dynamic nature of relatedness, the choice of what relatedness indicator to apply and how deserves more consideration than it is usually given. We hope that drawing attention to the qualitative differences between various relatedness linkages allows us, among other things, to initiate a discussion on the strengths and weaknesses of revealed relatedness indicators and their suitability for empirical analysis of regional development.

Glaeser et al. (1992) gave rise to the lively debate – commonly referred to in the literature as 'MAR vs. Jacobs' – on the impact of specialisation and diversification in industrial structures on regional economic growth. MAR refers to the theories of Marshall, Arrow, and Romer which suggest that knowledge spillovers take place predominantly between similar economic activities and give rise to localisation economies as a source of regional growth. In contrast, Jacobs (1969) claims that regional growth is fuelled by the recombinant process of knowledge generation that builds on a pre-existing variety of knowledge that is combined in new ways. The empirical evidence on the issue has remained largely inconclusive (de Groot, Poot, and Smit 2016), leading to the claims that the theoretical notions of specialisation and diversification are too simplistic to capture the relationship between regional industry structure and economic growth (Content and Frenken 2016).

In an attempt to resolve this empirical controversy, Frenken, Van Oort, and Verburg (2007) decompose the overall diversity in the regional industry structure into the variety in cognitively similar ("related variety") and distant ("unrelated variety") industries. They propose that related variety fosters regional growth as inter-industry knowledge spillovers occur more easily between different but cognitively similar industries. In contrast, fundamentally different knowledge bases in unrelated industries make effective knowledge transfer difficult (Noteboom 2000). This hypothesis has inspired a large number of empirical studies on the relationship between related variety and regional economic growth. Many of these studies have provided the support for the claim that related variety fosters growth in regional employment, value added, and productivity (Content and Frenken 2016).

The majority of studies in this stream of the literature have employed the measure of related variety based on the hierarchical structure of official industry classifications (e.g., NACE). The main underlying assumption is that two industries are more closely related to each other when they share more digits in the industry classification. In other words, classification-based relatedness between industries is defined as the number of initial digits that industries have in common. The fundamental weakness of this approach is that by assuming cognitive similarity to exist only within the same group of the industry classification it underestimates potential channels for knowledge spillovers and, thus, the breadth of possible linkages between industries (Bishop and Gripaios 2010; Firgo and Mayerhofer 2017).

This led to the search for the new (empirical) ways to operationalise and estimate the similarity between industries, which became known as revealed industry relatedness. One strategy takes economies of scope as its point of departure. Assuming that different industries are combined in the same portfolio because of economies of scope among them, one can infer relatedness by analysing the co-occurrences of industries in portfolios of firms and plants (Bryce and Winter 2009; Neffke, Henning, and Boschma 2011). Similarly, relatedness can be measured by the co-occurrence of products in export portfolios of nations (Hidalgo et al. 2007). Another approach utilises resource-based indicators to capture the similarities of resources used in different industries. Here, it is suggested that industry relatedness is best revealed through the inter-industry flows of inputs (Essletzbichler 2015) and skills (Neffke and Henning 2013). The strength of revealed relatedness measures is that they do not make any *ex ante* assumptions on the structure of linkages between industries, which characterises the classification-based relatedness measures.

Furthermore, as technological frontier moves outward over time, new industries emerge, others die out, whereas the very nature of production process changes. This may result in the destruction of established linkages between previously related industries and the emergence of new ones between previously non-existing or unrelated industries (Martynovich 2016). In that respect, the whole network of related industries is reorganised over time. Contrary to the classification-based measures, revealed relatedness is (at least in principle) much better suited for capturing changes in industry linkages over time. This makes the latter also more appropriate for analysing the impact of industry structure on long-term regional performance.

Taking the latter claim as a departure point, we analyse the changes in relatedness linkages between industries over time and implications of these changes for the impact (and its interpretation) of related variety on the long-term regional performance. Specifically, we employ the skill relatedness measure developed by Neffke and Henning (2013) to estimate relatedness between Swedish industries for five sub-periods between 1991 and 2010. We investigate the properties of these linkages, positing the following research question:

> *RQ1: How stable are relatedness linkages between industries? What characterises stable and non-stable linkages?*

After analysing the properties of the network of related industries itself, we derive from it the regional skill relatedness indicator and investigate whether relatedness linkages with various degree of stability contribute differently to regional employment growth in Swedish regions. In other words, we address the following research question:

> *RQ2: How does related variety based on stable and non-stable linkages contribute to regional economic growth?*

Answering these research questions allows us to make a two-fold contribution to the literature. First, we demonstrate that relatedness linkages change considerably over time and thus find support to the speculation made in the literature that relatedness is dynamic. Second, we show that the evolution of relatedness linkages has implications for the impact of related variety on regional economic growth. Hence, differences in regional settings identified in previous studies are not the only factor that can give rise to the heterogeneous impact of related variety on regional growth, but so can qualitative characteristics of relatedness linkages between industries present in different regions. It follows that for studies of long-term growth the right choice of relatedness measure is crucial. In this respect, we demonstrate the advantage of revealed relatedness measures over the classification-based ones since the latter cannot capture the dynamic nature of relatedness that is necessary for more nuanced analysis of regional performance.

2. Industry linkages, related variety, and regional economic growth

2.1. Skill similarity as a measure of relatedness between industries

An important feature of contemporary labour markets is that workers, particularly skilled ones, possess highly specialised human capital as they invest heavily in education and training to acquire specific skills that allow them to carry out certain tasks (Neffke, Otto, and Weyh 2017). The specificity of human capital develops in several domains. Earlier contributions underlined that human capital, accumulated by a worker at a particular job, was specific to a firm where she was employed (Becker 1964). More recent work suggests that human capital is industry-specific (Neal 1995; Parent 2000; Sullivan 2010) or occupation-specific (Gathmann and Schönberg 2010; Kambourov and Manovskii 2009; Poletaev and Robinson 2008). Also, regional variations in production technologies may impact the accumulation of human capital

(Rigby and Essletzbichler 1997). These domains of human capital specificity may reinforce each other (Sullivan 2010).

Specificity of human capital is an important factor affecting job switch decisions (Elliott and Lindley 2006). Workers tend to switch to jobs where they incur fewer shortages (skills to be acquired) and smaller redundancies (skills not needed anymore) in their human capital (Neffke and Nedelkoska 2010; Neffke, Otto, and Weyh 2017). In other words, when switching jobs, workers tend to maximise the opportunity to reuse their skills. This may be achieved if workers search for employment in industries that value skill portfolios similar to those in the previous industry of employment. Therefore, an overlap in skill requirements across different industries facilitates the inter-industry worker reallocation, while the lack of such overlap may constrain it. Thus, labour flows should be larger between industries with bigger overlap in skill requirements – or, skill related industries.

Flipping this argument, Neffke and Henning (2013) suggest that the existence of large labour flows between two industries may signal that these industries are skill related. That is, industry relatedness can be inferred from the analysis of labour flows. A recent investigation by Neffke, Otto, and Weyh (2017) demonstrates that industry relatedness derived in this way is a reliable measure since it (1) is remarkably stable over time as well as across occupations and wage levels; (2) does not reflect just the industrial composition of local economies but is a more generic measure; (3) is not simply a reflection of worker reallocation from shrinking to growing industries; and, (4) outperforms alternative relatedness measures in predicting entry and growth rates of local industries. In other words, skill relatedness is a powerful predictor for understanding economic dynamics.

There is one reservation, however. As Neffke, Otto, and Weyh (2017) themselves acknowledge, the study covers a rather short time period (1999-2008). Hence, while skill relatedness does not change much in this period, more drastic changes may be expected over longer time horizons if we believe that technological change, macroeconomic fluctuations, educational system performance, etc. affect skill requirements of and skill availability for industries.

2.2. Related variety and regional heterogeneity

While the study focuses on how industry relatedness changes over time, its particular importance lies in demonstrating how these changes influence economic processes at the regional level. Consequently, an important question to ask is whether stability in relatedness linkages and the resulting evolution of related variety matters for regional economic growth.

The empirical research points, in general, to the positive relationship between related variety and regional economic growth (Content and Frenken 2016). However, the impact of related variety is heterogeneous across regions of different types. For example, van Oort, de Geus, and Dogaru (2015) compare metropolitan regions to other regions in the EU and find a significant positive relation between employment growth and related variety in the latter group and no relationship in the former one. Cortinovis and van Oort (2015) divide the EU regions into high-tech, medium and low-tech regimes. While (surprisingly) detecting a negative relationship between related variety and employment growth across all regions, the effect was positive for high-tech regions, which is in line with Hartog, Boschma, and Sotarauta (2012) findings for Finnish regions. More recently, Firgo and Mayerhofer (2017) demonstrate that the employment growth in urban regions benefits more from a diversified, but related economic structure, while other regions gain more momentum from a broad industrial variety.

These results suggest that the knowledge spillovers between related industries occur primarily in metropolitan and/or technology intensive settings. Possible explanation lies in the role of knowledge intensity of regional industry mixes: more knowledge spills over across related industries, when these industries are knowledge-intensive in the first place (Content and Frenken 2016). These are more likely to be found in large, dynamic regions (Chadwick, Glasson, and Smith 2008). On the other hand, in more peripheral regions locked in 'old' technological trajectories, spillovers between 'related' industries may not be enough to stimulate growth (Firgo and Mayerhofer 2017). On a more general level, this suggests that it is crucial to differentiate between levels of regional hierarchy to capture the impact of related variety.

One important note is that Firgo and Mayerhofer (2017) compare the classification-based related variety measure to the co-occurrence-based measure used by Boschma, Minondo, and Navarro (2012) and demonstrate that the latter explains regional growth in a better way. This provides another motivation for our intention to use the measure of related variety based on revealed relatedness to analyse regional employment growth patterns.

3. Data and definitions

Data employed in the paper come primarily from the *Longitudinal Integration Database for Health Insurance and Labour Market Studies* (LISA). It is a longitudinal linked employer-employee database covering all individuals registered in Sweden (SCB 2016). It provides information on various dimensions of working life, connection to work, labour mobility, etc. 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 contains also the 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 1991 and 2010.

Classification of economic activities present in the regions is based upon the Statistical Classification of Economic Activities in the European Community (NACE) and its national implementation in Sweden (Swedish Standard Industrial Classification, SNI). During the period of observation, two versions of SNI are employed: SNI92 and SNI2002. The structure of these are summarised in Table 1 below.

Table 1. Comparison of two SNI classifications

	SNI92	SNI2002
Sections (1-digit)	17	17
Divisions (2-digit)	60	62
Groups (3-digit)	223	224
Classes (4-digit)	505	514
Sub-classes (5-digit)	755	774

As SNI2002 was a result of a minor revision of SNI92, it was no problem to establish unambiguous links between these two classification schemes to ensure the data consistency over time. The activity classifications were merged at the five-digit level with the resulting classification including 746 five-digit industries, which were further aggregated into 505 four-digit industries[1].

The location of individuals and establishments is recorded at the municipality level. For investigation purposes, 290 Swedish municipalities are merged into 90 local labour markets (as of 2000). The boundaries of these are defined by the statistics on commuting between municipalities in the way that maximises the self-containment of commuting flows. In other words, local labour market areas are defined in the way that maximises homogeneity of mobility patterns within a region while sustaining cross-regional heterogeneity (SCB 2010). Concerning labour market analysis, using local labour markets minimises the risk that the employment growth in a region will be affected by that of neighbouring regions.

To address the regional heterogeneity issue, the local labour markets are further aggregated into regional families. These are defined by the Swedish Agency for Economic and Regional Growth based on criteria such as the population size and density, regional business dynamics, share of individuals with higher education as well as access to higher education institutions (NUTEK 2004). Six regional families are defined. The highest three levels of the regional hierarchy are the Swedish metropolitan areas – Stockholm, Gothenburg, and Malmö. Remaining local labour markets are divided into the large regional centres, smaller regional centres, and peripheral regions.

4. Evolution of industry skill relatedness over time

Using the methodology proposed by Neffke and Henning (2013), we define skill relatedness as the presence of an excessive flow of labour between two industries. In particular, based on industry size, growth, and wage we estimate an expected flow $\widehat{F_{ij}}$ for each pair of four-digit industries i and j ($i \neq j$) using the zero-inflated negative binomial model. After that, we calculate the ratio of observed to predicted flows:

$$SR_{ij} = \frac{F_{ij}}{\widehat{F_{ij}}},$$

where F_{ij} is an observed flow of labour between industries i and j; $\widehat{F_{ij}}$ – expected flow of labour between the same industries. Here, values over 1 indicate skill relatedness[2 3 4].

Applying this procedure five times, we construct industry relatedness matrices for five time periods: 1991-1994, 1995-1998, 1999-2002, 2003-2006, 2007-2010. These time periods are not connected to any observable trends of the labour market development. Rather, the periodization is chosen in the way that allows us to divide the whole period under consideration into sub-periods of equal length. After this, to analyse the stability of relatedness ties between

[1] We excluded two five-digit industries coded 74501 (Labour placement agencies) and 74502 (Temporary employment agencies) since being formally employed in one of these industries might be non-indicative: a person classified as employed there might, in reality, work for or be lent to a firm in another industry.

[2] While there are no labour flows among the vast majority of industries, in many cases predicted labour flows are negligible as well. Hence, when $\widehat{F_{ij}}$ is only a fraction of one, an increase in the observed labour flow from zero to one individual may lead to a substantial increase in the ratio. This implies that skill relatedness is not estimated with equal precision for all industry combinations. Therefore, we construct confidence intervals to identify the excess labour flow which is significantly higher than 1.

[3] For the more detailed description of the methodology, consult the methodological supplement to Neffke and Henning (2013).

[4] Note that we impose no assumption on the symmetry of ties. That is, if industry i is related to industry j this does not necessarily imply that industry j is related to industry i.

industries, we divide all linkages into five categories:

- *stable ties* – those which existed in all five sub-periods;
- *disappearing ties* – those which existed only in the first two sub-periods;
- *emerging ties* – those which existed only in the last three sub-periods;
- *contingent ties* – those which existed in only in one sub-period;
- *miscellaneous ties* – the remaining ties that did not show any clear pattern.

Table 2 below provides an illustration of this classification.

Table 2. Types of related ties (examples)

Tie	1991-1994	1995-1998	1999-2002	2003-2006	2007-2010
Stable	R	R	R	R	R
Disappearing	R	R			
Emerging			R	R	R
Contingent		R			
Contingent				R	
Miscellaneous	R		R		R
Miscellaneous		R	R		R

Note: R indicates that the two industries are related in the respective time period

4.1. Stability of relatedness linkages

Table 3 below summarises the properties of skill relatedness linkages between industries in five time periods. The table is divided into three panels. First, we look at the general structure relatedness linkages. Second, we analyse the stability of related ties over five time periods. Finally, we examine the tie dynamics.

With respect to the general structure, the number of industries present in the Swedish economy remains rather stable, ranging from 497 to 501. This implies that there is only a minor variation in the number of possible industry linkages. Yet, the number of observed and related ties demonstrates a clear dynamic pattern. For instance, both increase rapidly between the first and third sub-periods and decrease somewhat afterwards. This pattern can be linked to the overall performance of the Swedish economy as in the early 1990s it experienced a rapid drop in employment followed by a fast recovery during the late 1990s until the economy slowed down again soon after the turn of the century.

When it comes to the stability and dynamics of linkages between industries, 1822 industry ties remain related over the whole time period, corresponding to between 23 and 29 per cent of related ties in different sub-periods. At the same time, approximately half of related industry linkages stay related in the previous and subsequent sub-periods (and even less of those remain related two sub-periods apart, both in the past and the future). Moreover, between 28.9 and 32.4 per cent of related industry linkages in each sub-period are contingent (that is, observed only in the respective sub-period). Finally, 379 related industry linkages observed in 1991-1998 vanished afterwards (disappearing ties), while 366 related industry combinations were not observed prior to 1999 but remained present after (emerging ties).

Table 3. Stability of relatedness linkages

	1991-1994	1995-1998	1999-2002	2003-2006	2007-2010
			General structure		
Number of industries	500	501	500	500	497
Possible ties	249500	250500	249500	249500	246512
Observed ties	27549	33422	40399	35374	37074
Observed, % of possible	11.0 %	13.3 %	16.2 %	14.2 %	15.0 %
Related ties	6167	7237	7993	7427	7369
Related ties, % of possible	2.5 %	2.9 %	3.2 %	3.0 %	3.0 %
Related ties, % of observed	22.4 %	21.7 %	19.8 %	21.0 %	19.9 %
			Stability of ties		
Ties observed in all time periods			10339		
% of observed in sub-period	37.5 %	30.9 %	25.6 %	29.2 %	27.9 %
Ties related in all time periods			1822		
% of related in sub-period	29.5 %	25.2 %	22.8 %	24.5 %	24.7 %
1991-1994 related ties	6167	3146	3054	2840	2736
% of related in 1991-1994	100.0 %	51.0 %	49.5 %	46.1 %	44.4 %
1995-1998 related ties	3146	7237	3834	3429	3261
% of related in 1995-1998	43.5 %	100.0 %	53.0 %	47.4 %	45.0 %
1999-2002 related ties	3054	3834	7993	3864	3659
% of related in 1999-2002	38.2 %	48.0 %	100.0 %	48.3 %	45.8 %
2003-2006 related ties	2840	3429	3864	7427	3800
% of related in 2003-2006	38.2 %	46.2 %	52.0 %	100.0 %	51.2 %
2007-2010 related ties	2736	3261	3659	3800	7369
% of related in 2007-2010	37.1 %	44.3 %	49.7 %	51.6 %	100.0 %
			Tie dynamics		
Contingent related ties, total			11130		
Contingent related ties, sub-period	1992	2093	2478	2182	2385
% of related in sub-period	32.3 %	28.9 %	31.0 %	29.4 %	32.4 %
Emerging ties				366	
% of related in sub-period			4.6 %	4.9 %	4.0 %
Disappearing ties	379				
% of related in sub-period	6.2 %	5.2 %			
Miscellaneous ties	1974	2943	3327	3057	2796
% of related in sub-period	32.0 %	40.7 %	41.6 %	41.2 %	37.9 %

These findings indicate that relatedness linkages between industries are very volatile over time. In that respect, considering the longer time period and looking through a different lens, our findings question those of Neffke, Otto, and Weyh (2017) who claim that relatedness linkages between industries remain rather stable over time. An interesting question then is whether the volatility in relatedness linkages is driven by the specificity of its derivation: labour flows are pro-cyclical (Burgess and Turon 2010; Fujita and Nakajima 2016), meaning that the fluctuation in the number of related industries might be driven by the macroeconomic performance of the Swedish economy. Indeed, the total number of related ties in different sub-periods seems to co-vary with the business cycle in Sweden. It is then possible that some ties just reflect the relocation of workers from shrinking to growing industries, or between industries with different levels of wages. To check whether this is the case, we investigate further characteristics of different types of ties.

4.2. Properties of stable and non-stable related ties

In Table 4, we look at the characteristics of the source and destination industries across five different types of related ties.

Table 4. Characteristics of industries with different tie types (averages, weighted by the number of ties)

Sub-period	Relatedness type	# of source industries	# of destination industries	Employment in source industry	Employment in destination industry	Employment growth in source industry	Employment growth in destination industry	Median wage in source industry	Median wage in destination industry
1991-1994	**Stable**	296	289	86933	90125	-0,028	-0,024	158982	160812
1995-1998	**Stable**	296	289	86078	89619	0,025	0,027	188074	190083
1999-2002	**Stable**	296	289	94168	98675	0,012	0,012	218462	221290
2003-2006	**Stable**	296	289	98096	102900	0,012	0,014	247249	250325
2007-2010	**Stable**	296	289	105342	110994	-0,003	0,000	285044	288812
1999-2002	**Emerging**	194	194	57129	56559	0,024	0,030	221121	217528
2003-2006	**Emerging**	194	194	60203	60702	0,015	0,017	249009	245771
2007-2010	**Emerging**	194	194	64869	67112	-0,002	0,001	286441	282748
1991-1994	**Disappearing**	215	225	80397	54693	-0,040	-0,038	158059	156199
1995-1998	**Disappearing**	215	225	74020	54717	-0,006	0,019	188089	186177
1991-1994	**Miscellaneous**	369	367	53187	60930	-0,034	-0,031	158421	156917
1995-1998	**Miscellaneous**	388	387	54586	53789	0,020	0,028	189020	190646
1999-2002	**Miscellaneous**	396	397	57554	61320	-0,005	0,001	218327	220109
2003-2006	**Miscellaneous**	389	395	56095	62724	0,000	0,008	248609	249434
2007-2010	**Miscellaneous**	383	381	57232	64794	-0,013	-0,007	288307	289549
1991-1994	**Contingent**	388	397	50474	46556	-0,050	-0,043	156185	156277
1995-1998	**Contingent**	402	402	35084	31150	0,011	0,016	188368	189674
1999-2002	**Contingent**	399	404	31636	35077	-0,010	0,003	216174	217641
2003-2006	**Contingent**	391	389	32188	34097	-0,012	-0,003	245098	242172
2007-2010	**Contingent**	403	397	37024	38328	-0,016	-0,013	288136	286809

Table 4 shows that industries linked by stable ties are on average much larger than industries connected by other types of ties. The size of source and destination industries differs significantly only for disappearing ties. Source industries for the latter are on average larger and grow slower than destination industries. The only other significant difference in growth of source and destination industries is observed for contingent ties in 1999-2006. In other cases, we find no substantial difference between source and destination industries in size, employment growth and median wage. Therefore, we can conclude that the business cycle-driven differences between source and destination industries are unlikely to be the primary reason for the volatility in relatedness linkages.

Another interesting question is to what extent the revealed relatedness derived from labour flows overlaps with classification-based one. To address it we look at number of digits shared by related industries of different type (Table 5).

Table 5. Characteristics of different types of ties

Tie type	Shared 3-digit code	Shared 2-digit code	Shared 1-digit code	Symmetrical ties	Symmetrical ties (of the same type)
Stable	13%	34%	53%	91%	72%
Disappearing	4%	18%	34%	40%	8%
Emerging	5%	20%	39%	61%	11%
Contingent	2%	10%	26%	17%	9%
Miscellaneous	6%	21%	39%	53%	32%
Total	6%	20%	38%	52%	34%

We see that overall only 20 per cent of the related ties are between industries that share the same two-digit code[5]. While industries with stable ties tend to share more digits, only 1 out of 10 industry pairs linked by contingent tie share a two-digit code. This implies that classification-based relatedness overestimates the linkages between industries belonging to the same two-digit group[6], and besides it underestimates other potential channels of relatedness. This confirms our initial expectations.

Furthermore, almost all stable ties are symmetrical. That is to say, ties exist from both industry A to B and the other way around, from B to A. 72 per cent of these two-way ties are stable in both directions. Overall, about half of all ties are symmetrical with the exact degree of symmetry in close range of this for disappearing, emerging, and miscellaneous ties (40-61 per cent). Only contingent ties have a considerably lower symmetry (17 per cent). Moreover, only about 10 per cent of disappearing and emerging ties are of this respective type in both directions. These findings can either mean that most disappearing ties never were symmetrical and are hence less likely to have belonged to the stable tie category in the past, or that the changes in skill relatedness linkages are not symmetrical (i.e. symmetrical counterparts of these ties disappeared in earlier periods). Either way, this points to that skill requirements in terms of similarities untangle asymmetrically. The conclusion is similar for emerging ties, which form typically only in one direction at a time. These patterns are another argument in favour of using revealed relatedness measures over classification-based ones, which treat all ties as symmetrical.

5. Related variety at the regional level

5.1. Constructing the skill-based measure of regional related variety

After investigating inter-temporal variation in skill relatedness matrices *per se*, we analyse the implications this variation has for the analysis of regional economic development. To do that, we calculate the regional skill relatedness indicator proposed by Fitjar and Timmermans (2017):

$$RSR_r = \frac{\left(\sum_{i=1}^{N} \left(\frac{d_i}{2}\right) \sqrt{P_{ir}}\right)/N_r}{\left(\sum_{i=1}^{N} \sqrt{P_{ir}}\right)/N_r}$$

[5] In classification-based measures industries belonging to the same two-digit code are conventionally considered related.

[6] While it is unreasonable to expect that all industries sharing a 2-digit code could be identified as related given the size of labour flows in Sweden, the low share of industry pairs within 2-digit code identified as related warrants this claim.

where d_i – a number of incoming and outgoing related ties for each industry i present in a region r (according to the skill relatedness matrix); P_{ir} – a share of industry i in the regional employment; N_r – a number of industries present in the region.

We further decompose this indicator into several components in the following way:

$$RSR_r = \frac{\left(\sum_{i=1}^{N}\left(\frac{d_i}{2}\right)\sqrt{P_{ir}}\right) / N_r}{\left(\sum_{i=1}^{N}\sqrt{P_{ir}}\right) / N_r} = \frac{\left(\sum_{i=1}^{N}\left(\frac{d_i^{stable} + d_i^{disap} + d_i^{emerg} + d_i^{misc} + d_i^{cont}}{2}\right)\sqrt{P_{ir}}\right) / N_r}{\left(\sum_{i=1}^{N}\sqrt{P_{ir}}\right) / N_r} =$$

$$= RSR_r^{stable} + RSR_r^{disap} + RSR_r^{emerg} + RSR_r^{misc} + RSR_r^{cont}$$

where $RSR_r^{stable}/RSR_r^{disap}/RSR_r^{emerg}/RSR_r^{misc}/RSR_r^{contin}$ is the regional skill relatedness based on the stable/disappearing/emerging/miscellaneous/contingent ties respectively.

5.2. Analysing the impact of the regional skill relatedness on employment growth

After that, we estimate the regression relating regional employment growth to regional skill relatedness and its various components using the following fixed effects model:

$$\Delta emp_{rt+3} = \alpha + RSR_{rt}\beta_1 + CONTROL_{rt}\beta_2 + \delta_r + \theta_t + u_{rt}$$

where Δemp_{rt+3} – the vector of annual employment growth in region r during each sub-period t where $t \in \{1991, 1995, 1999, 2003, 2007\}$; RSR_{rt} – the matrix of regional skill relatedness measures for region r in the beginning of each sub-period; $CONTROL_{rt}$ – the matrix containing control variables. The term δ_r accounts for regional fixed effects controlling for time-invariant unobservable regional characteristics; θ_t represents region-invariant unobservable time effects; and u_{rt} captures the remaining disturbances[7].

In addition to the key variable of interest we include the number of control variables:

Specialisation: following van Oort, de Geus, and Dogaru (2015) and Firgo and Mayerhofer (2017), we include the Theil index (sum of location quotients of the SNI two-digit industries weighted by their employment shares within a region) as a control for the level of specialisation. This index transforms the individual sectoral concentration measures into a generalised between-region specialisation measure.

Wage level: the median regional wage level is included to control for general economic convergence. It is expected that employment will, ceteris paribus, grow more rapidly in regions with lower economic development (and, thus, lower median wage) levels.

Population density: this variable controls for general effects from the spatial agglomeration of economic activity. It thus reflects the urbanisation economies not linked to the industry structure.

[7] As a robustness check, we estimate the same regression using four periods, which are five years long each. The results confirm our findings, but are not reported here. They are available from the authors upon request.

Competition: this variable controls for competition between firms within the region. It is measured as an inverse of the number of employees per firm.

Employment share in manufacturing: this variable controls for effects on employment growth associated with region's structural orientation (manufacturing vs services).

Share of workers with higher education (within the group of workers aged 25+): this variable measures human capital effects on regional employment dynamics.

In addition, in this part of the analysis we merge the three highest regional hierarchy levels (all representing single labour market region) into one region type called "core regions", ending up with four region types in total.

Table 6 below provides the descriptive statistics for variables included in the analysis.

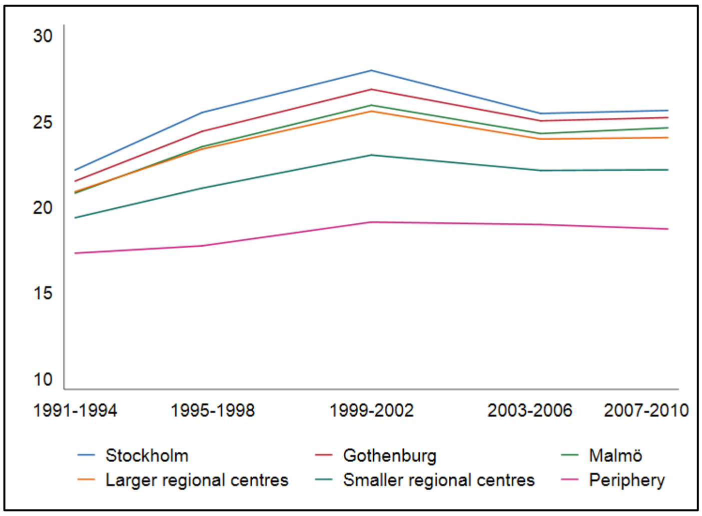
Table 6. Descriptive statistics for dependent and explanatory variables

Variable	N	Mean	St. dev.	Min	Max
Employment growth	450	-0.01	0.02	-0.07	0.03
RSR	450	20.59	3.06	12.86	28.07
RSR_{stable}	450	7.90	0.61	5.67	9.15
RSR_{disap}	180	1.08	0.13	0.75	1.30
RSR_{emerg}	270	1.04	0.19	0.39	1.33
RSR_{misc}	450	7.82	1.75	3.93	11.98
RSR_{cont}	450	3.82	1.04	1.35	5.92
Specialisation	450	0.32	0.21	0.04	1.22
Median wage	450	186637	40681	111500	274656
Population density	450	24.17	29.04	0.24	175.70
Competition	450	0.13	0.03	0.07	0.23
Employment share of manufacturing	450	0.23	0.10	0.02	0.57
Share of workers with higher education	450	0.19	0.05	0.09	0.39

5.3. Changes in regional skill relatedness over time

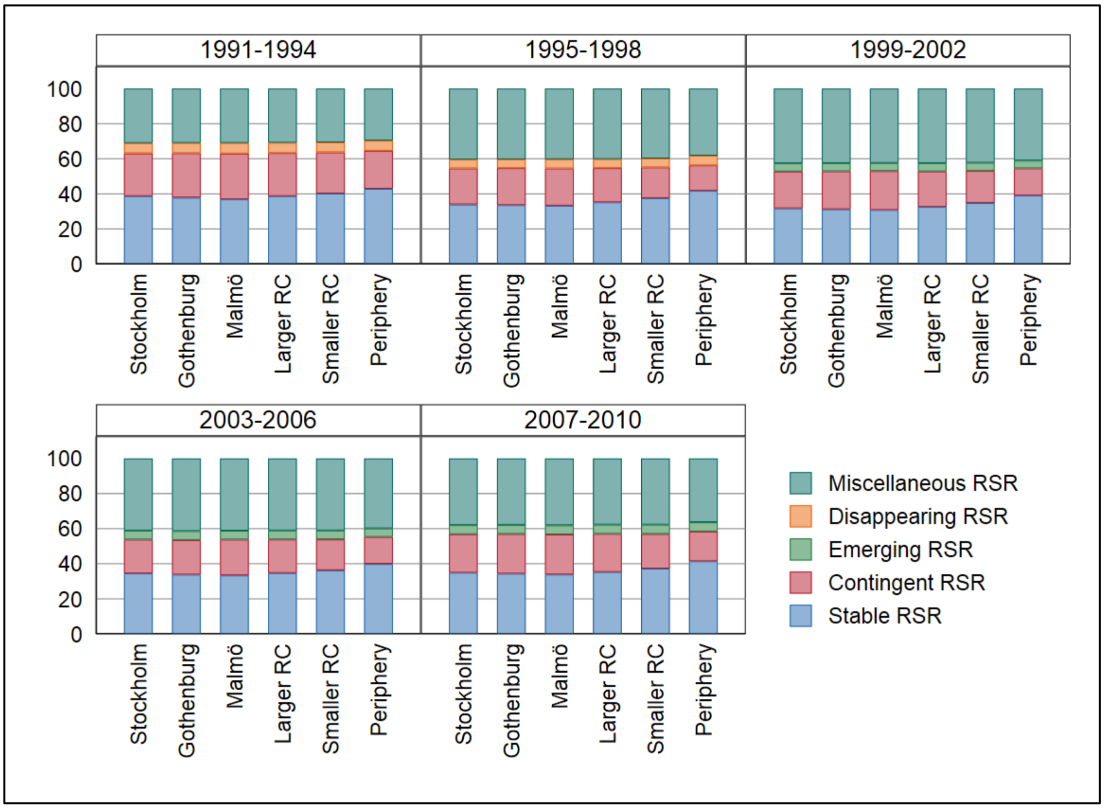
As it is expected, the regional skill relatedness increases with the level of regional hierarchy (Figure 1).

Figure 1. Change in total RSR 1991-2010



This ranking is not caused by any particular RSR component since all components represent on average similar shares at various hierarchy levels and this pattern has remained unchanged over the two decades (Figure 2).

Figure 2. Composition of RSR by regional type (%)



The largest components are stable RSR and miscellaneous RSR, each contributing 35-40 per cent of total RSR. RSR based on disappearing and emerging ties both contribute around five per cent, while contingent RSR makes up the remaining 20 per cent. Hence, in terms of magnitude, the stable, miscellaneous and contingent RSR have the highest potential to support regional growth.

In addition, RSR in different regional families follows a similar dynamic pattern (Figure 1), which is more pronounced in core and large regions. While total RSR increased by 10-20 per cent at all regional levels over 20 years, the growth pace was slower in smaller regions. The hump-like pattern observed for total RSR is mainly driven by contingent and miscellaneous RSR, because stable, emerging and disappearing RSR follow clear upward or downward trends (see Appendix for more details). This suggests that the pattern is shaped by changes in the skill relatedness linkages and not only by the changes in regional industry structures that are the sole cause for variation in the latter types of RSR. Once again, the importance of using relatedness indicators that allow changes in ties over time is maintained.

5.4. The impact of the regional skill relatedness on the regional employment growth

The regression results confirm the findings of many previous studies that related variety tends to have a positive impact on the regional employment growth (Table 7). However, we also find that this impact varies considerably between different components of RSR and at different levels of regional hierarchy.

Table 7. Regression results

Dependent variable = employment growth	Total RSR			Stable RSR		Emerging RSR		Disappearing RSR		Contingent RSR	
	Model 1	Model 2	Model 3	Model 4	Model 5	Model 6	Model 7	Model 8	Model 9	Model 10	Model 11
RSR (ref: metropolitan areas)	0.0245	0.0437**	0.0679***	0.0299	0.0580	0.0101	0.1299*	0.0856**	-0.7387***	0.0194**	0.0350*
	(0.0190)	(0.0190)	(0.0222)	(0.0235)	(0.0757)	(0.0149)	(0.0713)	(0.0341)	(0.1499)	(0.0076)	(0.0181)
Larger regional centres			0.0004		0.0739		-0.0797		0.5805***		-0.0166
			(0.0152)		(0.0689)		(0.0665)		(0.1738)		(0.0135)
Smaller regional centres			-0.0370*		-0.0519		-0.1023		0.7281***		-0.0138
			(0.0199)		(0.0758)		(0.0705)		(0.1587)		(0.0152)
Periphery			-0.0371*		-0.0294		-0.1233*		0.8763***		-0.0157
			(0.0221)		(0.0771)		(0.0739)		(0.1534)		(0.0152)
Specialisation	-0.0093***	-0.0116***	-0.0121***	-0.0108***	-0.0111***	-0.0107***	-0.0109***	-0.0114***	-0.0116***	-0.0119***	-0.0119***
	(0.0033)	(0.0035)	(0.0033)	(0.0033)	(0.0034)	(0.0034)	(0.0034)	(0.0033)	(0.0033)	(0.0033)	(0.0033)
Median wage		-0.0109	-0.0082	-0.0168	-0.0160	-0.0099	-0.0078	-0.0048	-0.0015	-0.0034	-0.0026
		(0.0405)	(0.0401)	(0.0418)	(0.0416)	(0.0405)	(0.0409)	(0.0404)	(0.0412)	(0.0421)	(0.0423)
Population density		-0.0078	-0.0170	0.0047	-0.0036	0.0067	0.0023	0.0067	0.0074	-0.0082	-0.0086
		(0.0191)	(0.0214)	(0.0181)	(0.0204)	(0.0187)	(0.0227)	(0.0178)	(0.0192)	(0.0203)	(0.0207)
Employment share of manufacturing		0.0993***	0.0939***	0.0902***	0.0916**	0.0717***	0.0735***	0.0805***	0.0814***	0.0855***	0.0856***
		(0.0284)	(0.0290)	(0.0343)	(0.0353)	(0.0255)	(0.0255)	(0.0280)	(0.0282)	(0.0249)	(0.0250)
Share of workers with higher education		0.0369	0.0318	0.0095	0.0071	0.0247	0.0071	0.0005	-0.0042	0.0391	0.0405
		(0.0687)	(0.0695)	(0.0669)	(0.0669)	(0.0678)	(0.0677)	(0.0662)	(0.0701)	(0.0729)	(0.0737)
Competition		0.0715***	0.0671***	0.0706***	0.0694***	0.0725***	0.0719***	0.0735***	0.0740***	0.0722***	0.0725***
		(0.0132)	(0.0133)	(0.0137)	(0.0139)	(0.0141)	(0.0144)	(0.0135)	(0.0140)	(0.0131)	(0.0132)
Regional fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Sub-period fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
N	450	450	450	450	450	270	270	180	180	450	450
R^2	0.807	0.831	0.833	0.829	0.830	0.628	0.631	0.915	0.923	0.832	0.832

Note: Robust standard errors clustered at the regional level are reported in brackets. ***(**,*) indicate a significant difference from 0 at 1% (5%, 10%) level.

Total RSR appears to be correlated with the higher regional employment growth (Model 2). This relationship is more pronounced in larger, more dynamic regions, while it is somewhat mitigated in smaller regional centres and peripheral regions (Model 3).

When it comes to the components of RSR, the first observation is that stable RSR does not have any significant impact on the regional employment growth, irrespective of the level of the regional hierarchy (Models 4 and 5). This finding is important as stable RSR represents the largest share of the total RSR. Emerging RSR tends to have a positive impact on the regional employment growth, but mostly in the metropolitan regions, while this impact disappears for ones that are more peripheral (Models 6 and 7). This implies that only large dynamic regions, being the technology-intensive settings, can benefit from the newly emerging industry linkages. On the contrary, disappearing RSR is beneficial only in the regions at the lowest levels of the regional hierarchy, while having a negative impact in core regions (Models 8 and 9). This suggests that the peripheral regions may still benefit from related industry mix even if the linkages between industries involved are dissolving[8]. Finally, contingent RSR tends to have a small positive impact on regional employment growth in all regions (Models 10 and 11).

6. Discussion

One of our key findings is that the relatedness linkages between industries change considerably over time. Only a quarter of ties remained related for 20 years, while around 30 per cent were related only during one four-year sub-period. This finding supports the claim made in the literature that relatedness is dynamic and raises the question how good we are capturing it (Boschma 2017; Castaldi, Frenken, and Los 2015; Desrochers and Leppälä 2011).

Leaving aside the inevitable noise, there are several developments that may lead to changes in relatedness linkages. Besides the change in skill requirements of or similarities between industries, which is of the main concern here, the macroeconomic conditions (i.e., the labour flows fluctuation due to the business cycle) and structural change (i.e., entry and exit as well as rise and fall of certain industries) may have an impact. In case of Sweden, the entry and exit of industries was negligible and we accounted for, at least some of, the industry dynamics by using parametrical approach to identify the relatedness linkages. Yet, the exact impact of macroeconomic conditions and noise on the dynamics of skill relatedness remains to be addressed in further research.

The stability of ties relates closely to whether the matrix represents largely past, current or potential future relatedness linkages. Matrix of related industries itself is a snapshot in time, but for some measures the lens is focused on the past, while for others it is pointed towards the future. A fast adjusting skill relatedness indicator (in its decomposed form) is likely to pinpoint the linkages that are valuable *right now*, although these can only be inferred from the data with considerable delay. Relatedness measures based on technological knowledge (e.g., patents) are more forward-looking, allowing to detect the potential relatedness ties (which might or might not be realised), while co-location-based measures (e.g., export portfolios) reflect the past development paths. Classification-based measures in their turn do not have any time stamp at all. This implies that the suitability of relatedness indicator depends on the addressed issue. For example, in designing diversification policies for future

[8] Note that the impact of disappearing and emerging RSR is only estimated for the relevant time periods.

regional growth it is important that the chosen type of relatedness reflects linkages that are likely to retain relevance in the coming years.

Apart from the 'age', five types of relatedness linkages identified in this study differ in other important ways. Disappearing ties are linked to industries with slow growth at the national level, while stable ties are associated with larger than average industries. This makes it hard to distinguish empirically between the impact of substantial changes in relatedness and industry characteristics on employment growth unless one focuses on the micro-level processes at the industry, plant or individual level. Nevertheless, given that most industries have several types of ties, it is the type and number of ties that an industry has that is likely to matter more for the impact related variety has on economic performance at the regional and national level.

Usually, including in this paper[9], related variety is derived from symmetrical relatedness (Boschma 2017). Our results, however, show that only half of the ties are indeed symmetrical and the degree of symmetry varies by the type of a linkage. For the most dynamic tie types (i.e., disappearing, emerging and contingent ties) the asymmetry is rather high. In other words, the emergence and untangling of relatedness is to a great extent unidirectional. Boschma (2017) argues that the asymmetry of ties might matter for regional diversification. Our results suggest that, in addition, the asymmetrical nature of ties might also be relevant for studies on regional growth. Leaving aside the stable ties, which are mostly symmetrical, for other types of ties the incoming and outgoing linkages of an industry belong to different tie types. This, in turn, means that their impact on growth is likely also different, as our analysis has shown.

On the whole, the empirical investigation of the impact of related variety (captured by the regional skill relatedness) on regional employment growth confirms the findings of previous studies (for a review of the literature, see Content and Frenken 2016). That is, related variety is positively associated with regional growth. What we add to the literature is demonstrating that this impact is heterogeneous in different types of regions and for different components of related variety.

For instance, the positive impact of overall related variety is stronger in larger, more dynamic regions and weaker in ones that are more peripheral. This is in line with Cortinovis and van Oort (2015) and Firgo and Mayerhofer (2017) findings that urban and technologically-intensive regions gain more from related variety.

At the same time, related variety based on stable linkages does not have any significant impact on the regional employment growth in any type of region. Related variety based on emerging linkages has an impact mostly in metropolitan areas, while the opposite is true for the one based on disappearing linkages. Finally, related variety based on contingent ties tends to contribute positively to the regional employment growth in all regions. These findings suggest that the heterogeneous impact of related variety on regional growth, identified in previous studies, might stem not only from the difference in regional settings *per se*, but also from the qualitative characteristics of the relatedness linkages between industries.

An important point here is that untangling relatedness at the national level masks potential heterogeneity in industry linkages at different levels of the regional hierarchy. We know that

[9] While our relatedness matrix consists of directional ties, our research design does not distinguish between incoming and outgoing ties in their impact on regional growth.

the essence of activities under the same industry code may vary by regional type (Storper et al. 2015; Lundquist and Olander 2001). In other words, while relatedness based on labour flows at the national level might classify two industries as not related, in certain regions these industries might still gain from each other's presence. This might, at least partly, explain why the impact of related variety based on various kinds of ties varies by the level of the regional hierarchy.

One particularly alarming observation is that, although related variety based on stable ties makes up one third of the total related variety, we find no evidence that this component contributes to growth. While identifying reasons why this is so lays beyond the scope of this study, we propose two plausible explanations. First, industries involved might have relatively low knowledge spillover potential. Second, these industries might have already used up their knowledge spillover potential in the past as these are likely to represent large mature industries, or that the types of innovation in mature stages on product life cycle lead rather to labour saving than employment growth[10].

To sum up, relatedness linkages have a 'best before date' so that their impact on growth depends on their 'age'. In this respect, it is not only the emergence and disappearance of relatedness linkages that might have implications for growth potential of regions, but also the exhaustion of knowledge spillover potential between industries which remain related (Boschma 2017).

7. Conclusion

All in all, not all relatedness is created equal. We demonstrate that relatedness linkages change considerably over time and that these changes have implications for the impact of related variety on regional economic growth. It follows that the choice of what kind of relatedness measure to use is crucial in studies of long-term growth.

The common concern with using classification-based relatedness measures has been that these are not picking up all relatedness linkages (Firgo and Mayerhofer 2017). Our results support this concern. We demonstrate that not only such indicators underestimate possible channels of relatedness, but they also overestimate the linkages between industries belonging to the same industry group. We also indicate another major drawback of using classification-based measures – namely, that these to a large extent remain fixed over time and are not able to pick up the dynamic character of relatedness ties. Furthermore, we argue that by incorporating this dynamism the use of revealed measures of relatedness allows more nuanced analysis of regional performance. In this respect, we demonstrate the advantage of revealed relatedness measures over the classification-based ones.

7.1. Directions for future research

This paper underlines clearly the dynamic and evolving nature of relatedness (Boschma 2017; Desrochers and Leppälä 2011). We can fully agree with Castaldi, Frenken, and Los (2015, p. 777) that this is one of the "most interesting and challenging research avenues for the future". While we focused mostly on the stability of ties, other important issues fell out of the scope of the paper.

First, we only briefly touched upon the characteristics of industries linked by different types

[10] This means that stable ties might still contribute to the productivity growth at the regional level.

of ties. A more in-depth study of the qualities of different tie types may provide important insights into the mechanisms of tie formation and evolution over time.

Second, and related, the conceptual mechanisms of why and how different types of ties matter for growth deserve more attention. Looking at the micro-mechanisms of tie formation may allow deeper understanding of why related variety matters for regional growth. Moreover, while the aggregate growth outcomes might be the same for different ties or regional types, the particular channels through which related variety has an impact on regional growth may differ by tie type (Duranton and Puga 2004). This paper provides one new dimension (i.e., tie stability) to consider in growth studies leaving other conceptual questions unaddressed. It would be especially interesting to look at the interplay between the tie 'age' at the national level and the maturity of related ties in a particular local industry setting.

Third, when it comes to analysing revealed relatedness measures over time, a key concern is how to distinguish the actual change in relatedness linkages from the inevitable noise. It is crucial to continue working on the refinement of relatedness indicators with the aim of finding a balance between failing to pick up weak ties (but also ties in small industries) and the risk of introducing noise in the matrix.

Finally, in recent years it has become common to suggest related diversification as a 'natural' development path to achieve higher regional growth (Boschma 2017). Based on our findings of the qualitative differences between various related ties, it is important to study whether these differences in related diversification pathways (i.e. tie 'age') later on have an impact on growth. For example, whether diversification based on emerging ties is more beneficial than developments based on disappearing or stable ones. Another aspect to consider in assessing potential benefits of related versus unrelated diversification on growth is region's position in national hierarchy. If smaller, peripheral regions benefit only from certain type of related variety then advising them to follow only related diversification path without looking at the qualitative characteristics of created potential ties is unsubstantiated.

Acknowledgements

The authors are grateful for constructive advice and critical comments on earlier versions of this paper by Karl-Johan Lundquist, Markus Grillitsch, Ron Boschma, Frank Neffke, Martin Henning, and Cesar Hidalgo. The paper benefited from fruitful discussions at the The Umeå University Conference on Mobility, Economic Transformation and Regional Growth held in Stockholm on September 27-29, 2017, the 2018 Geography of Innovation conference held in Barcelona on January 30 – February 2, 2018, and Innovation, Economic Complexity and Economic Geography Workshop held in Cambridge, MA on August 5-7, 2018.

References

Becker, G. 1964. *Human Capital*. Chicago, IL: University of Chicago Press.

Bishop, P. and P. Gripaios. 2010. Spatial Externalities, Relatedness and Sector Employment Growth in Great Britain. *Regional Studies* **44:443-454**.

Boschma, R. 2017. Relatedness as driver of regional diversification: a research agenda. *Regional Studies* **51:351-364**.

Boschma, R.; A. Minondo; and M. Navarro. 2012. Related variety and regional growth in Spain*. *Papers in Regional Science* **91:241-256**.

Bryce, D.J. and S.G. Winter. 2009. A General Interindustry Relatedness Index. *Management Science* **55:1570-1585**.

Burgess, S. and H. Turon. 2010. Worker flows, job flows and unemployment in a matching model. *European Economic Review* **54:393-408**.

Castaldi, C.; K. Frenken; and B. Los. 2015. Related Variety, Unrelated Variety and Technological Breakthroughs: An analysis of US State-Level Patenting. *Regional Studies* **49:767-781**.

Chadwick, A.; J. Glasson; and H.L. Smith. 2008. Employment Growth in Knowledge-Intensive Business Services in Great Britain during the 1990s — Variations at the Regional and Sub-Regional Level. *Local Economy* **23:6-18**.

Content, J. and K. Frenken. 2016. Related variety and economic development: a literature review. *European Planning Studies* **24:2097-2112**.

Cortinovis, N. and F. van Oort. 2015. Variety, economic growth and knowledge intensity of European regions: a spatial panel analysis. *The Annals of Regional Science* **55:7-32**.

de Groot, H.L.F.; J. Poot; and M.J. Smit. 2016. Which Agglomeration Externalities Matter Most and Why? *Journal of Economic Surveys* **30:756-782**.

Desrochers, P. and S. Leppälä. 2011. Opening up the 'Jacobs Spillovers' black box: local diversity, creativity and the processes underlying new combinations. *Journal of Economic Geography* **11:843-863**.

Duranton, G. and D. Puga. 2004. Chapter 48 - Micro-Foundations of Urban Agglomeration Economies. In *Handbook of Regional and Urban Economics*, ed. J.V. Henderson and J.-F. Thisse, 2063-2117: Elsevier.

Elliott, R.J. and J. Lindley. 2006. Skill Specificity and Labour Mobility: Occupational and Sectoral Dimensions. *The Manchester School* **74:389-413**.

Essletzbichler, J. 2015. Relatedness, Industrial Branching and Technological Cohesion in US Metropolitan Areas. *Regional Studies* **49:752-766**.

Firgo, M. and P. Mayerhofer. 2017. (Un)related variety and employment growth at the sub-regional level. *Papers in Regional Science*.

Fitjar, R.D. and B. Timmermans. 2017. Regional skill relatedness: towards a new measure of regional related diversification. *European Planning Studies* **25:516-538**.

Frenken, K.; F. Van Oort; and T. Verburg. 2007. Related Variety, Unrelated Variety and Regional Economic Growth. *Regional Studies* **41:685-697**.

Fujita, S. and M. Nakajima. 2016. Worker flows and job flows: A quantitative investigation. *Review of Economic Dynamics* **22:1-20**.

Gathmann, C. and U. Schönberg. 2010. How General Is Human Capital? A Task-Based Approach. *Journal of Labor Economics* **28:1-49**.

Glaeser, E.L.; H.D. Kallal; J.A. Scheinkman; and A. Shleifer. 1992. Growth in Cities. *Journal of Political Economy* **100:1126-1152**.

Hartog, M.; R. Boschma; and M. Sotarauta. 2012. The Impact of Related Variety on Regional Employment Growth in Finland 1993–2006: High-Tech versus Medium/Low-Tech. *Industry and Innovation* **19:459-476**.

Hidalgo, C.A.; B. Klinger; A.-L. Barabási; and R. Hausmann. 2007. The Product Space Conditions the Development of Nations. *Science* **317:482-487**.

Jacobs, J. 1969. *The Economy of Cities*. New York: Vintage Books.

Kambourov, G. and I. Manovskii. 2009. Occupational Mobility and Wage Inequality. *The Review of Economic Studies* **76:731-759**.

Lundquist, K.-J. and L.-O. Olander. 2001. *Den glömda strukturcykeln. Ny syn på industrins regionala tillväxt och omvandling*. Institutionen för kulturgeografi och ekonomisk geografi, Lunds universitet.

Martynovich, M. 2016. *General purpose technology diffusion and labour market dynamics: A spatio-temporal perspective*. Lund: Media-Tryck.

Neal, D. 1995. Industry-specific human capital: Evidence from displaced workers. *Journal of Labor Economics* **13:653-677**.

Neffke, F. and M. Henning. 2013. Skill relatedness and firm diversification. *Strategic Management Journal* **34:297-316**.

Neffke, F.; M. Henning; and R. Boschma. 2011. How do regions diversify over time? Industry relatedness and the development of new growth paths in regions. *Economic Geography* **87:237-265**.

Neffke, F. and L. Nedelkoska. 2010. Human capital mismatches along the career path. In *Jena economic research papers No. 2010,051*. Jena: Leibniz Information Centre for Economics.

Neffke, F.M.H.; A. Otto; and A. Weyh. 2017. Inter-industry labor flows. *Journal of Economic Behavior & Organization* **142:275-292**.

Noteboom, B. 2000. *Learning and innovation in organizations and economies*. Oxford: Oxford University Press.

NUTEK. 2004. Analyser för regionalt utvecklingsarbete - En handbok med praktiska tips och metodexempel. Stockholm: Verket för näringslivsutveckling (NUTEK).

Parent, D. 2000. Industry-specific capital and the wage profile: Evidence from the national longitudinal survey of youth and the panel study of income dynamics. *Journal of Labor Economics* **18:306-323**.

Poletaev, M. and C. Robinson. 2008. Human capital specificity: evidence from the Dictionary of Occupational Titles and Displaced Worker Surveys, 1984–2000. *Journal of Labor Economics* **26:387-420**.

Rigby, D.L. and J. Essletzbichler. 1997. Evolution, Process Variety, and Regional Trajectories of Technological Change in U.S. Manufacturing. *Economic Geography* **73:269-284**.

SCB. 2010. *Lokala arbetsmarknader – egenskaper, utveckling och funktion*. Örebro, Sweden: SCB.

———. 2016. Longitudinell integrationsdatabas för Sjukförsäkrings- och Arbetsmarknadsstudier (LISA) 1990-2013. In *Arbetsmarknad och Utbildning Bakgrundsfakta 2016:1*. Örebro: SCB.

Storper, M.; T. Kemeny; N. Makarem; and T. Osman. 2015. *The Rise and Fall of Urban Economies: Lessons from San Francisco and Los Angeles*. Stanford: Stanford University Press.

Sullivan, P. 2010. Empirical evidence on occupation and industry specific human capital. *Labour Economics* **17:567-580**.

van Oort, F.; S. de Geus; and T. Dogaru. 2015. Related Variety and Regional Economic Growth in a Cross-Section of European Urban Regions. *European Planning Studies* **23:1110-1127**.

APPENDIX

Figure A1. Change in stable RSR 1991-2010

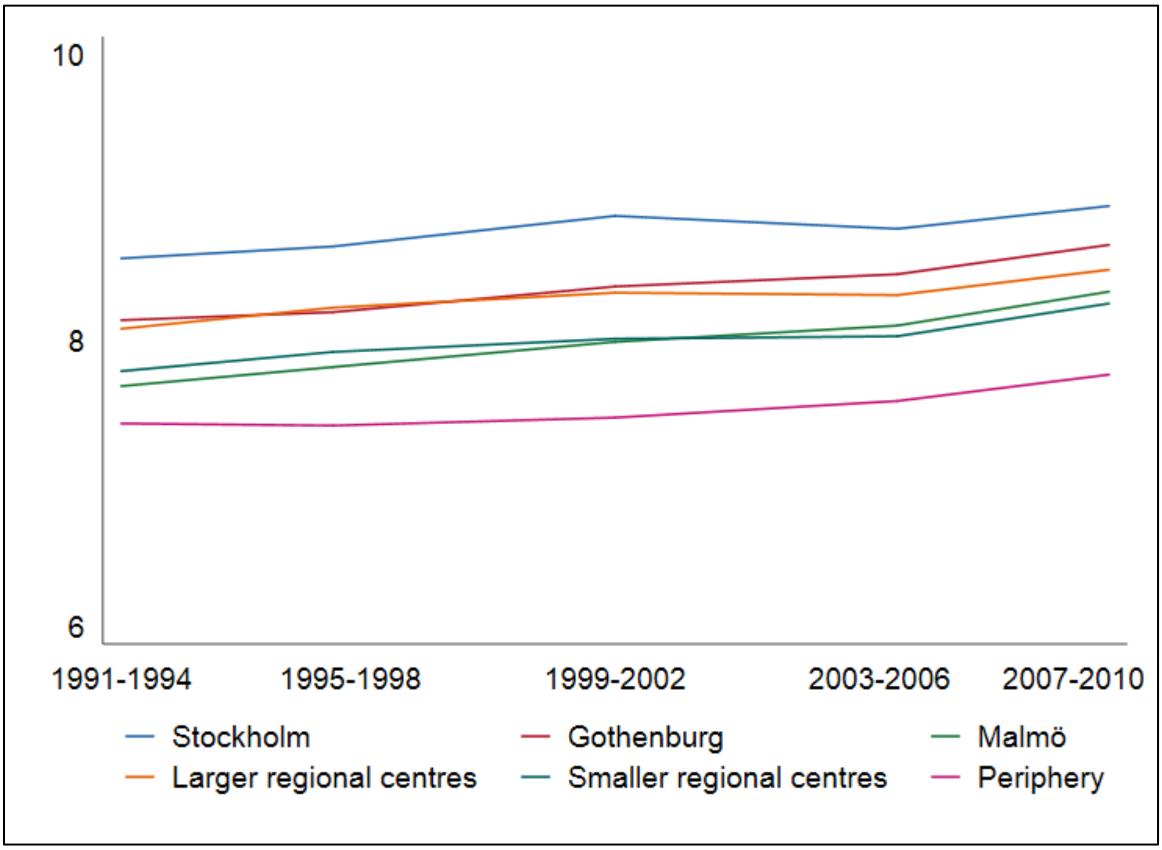


Figure A2. Change in emerging RSR 1991-2010

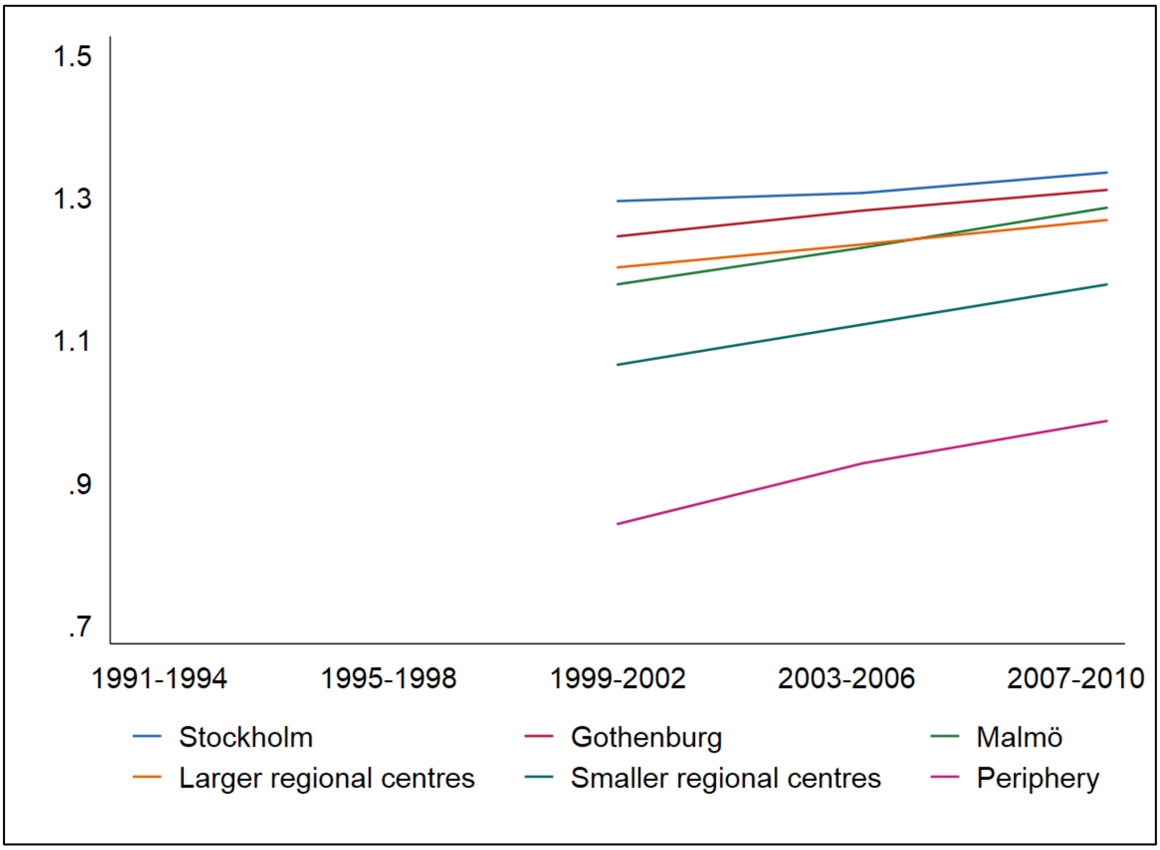


Figure A3. Change in disappearing RSR 1991-2010

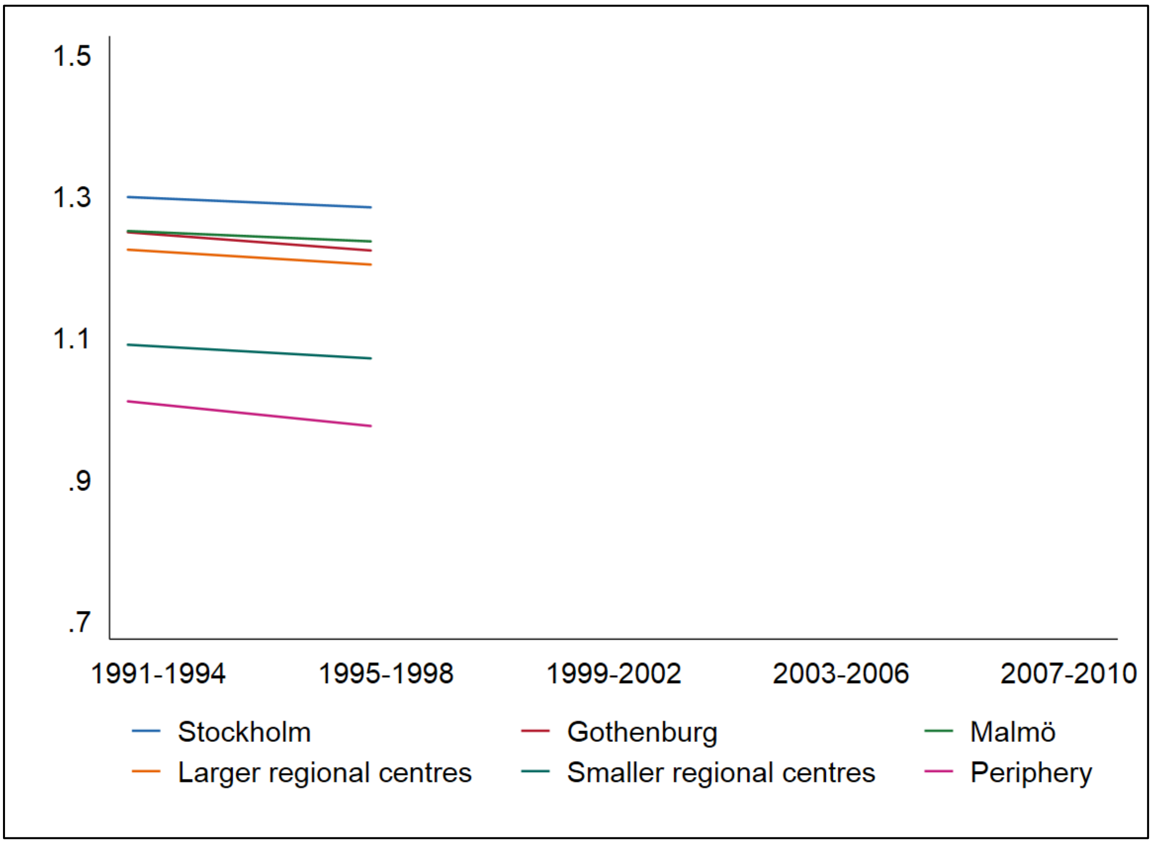


Figure A4. Change in contingent RSR 1991-2010

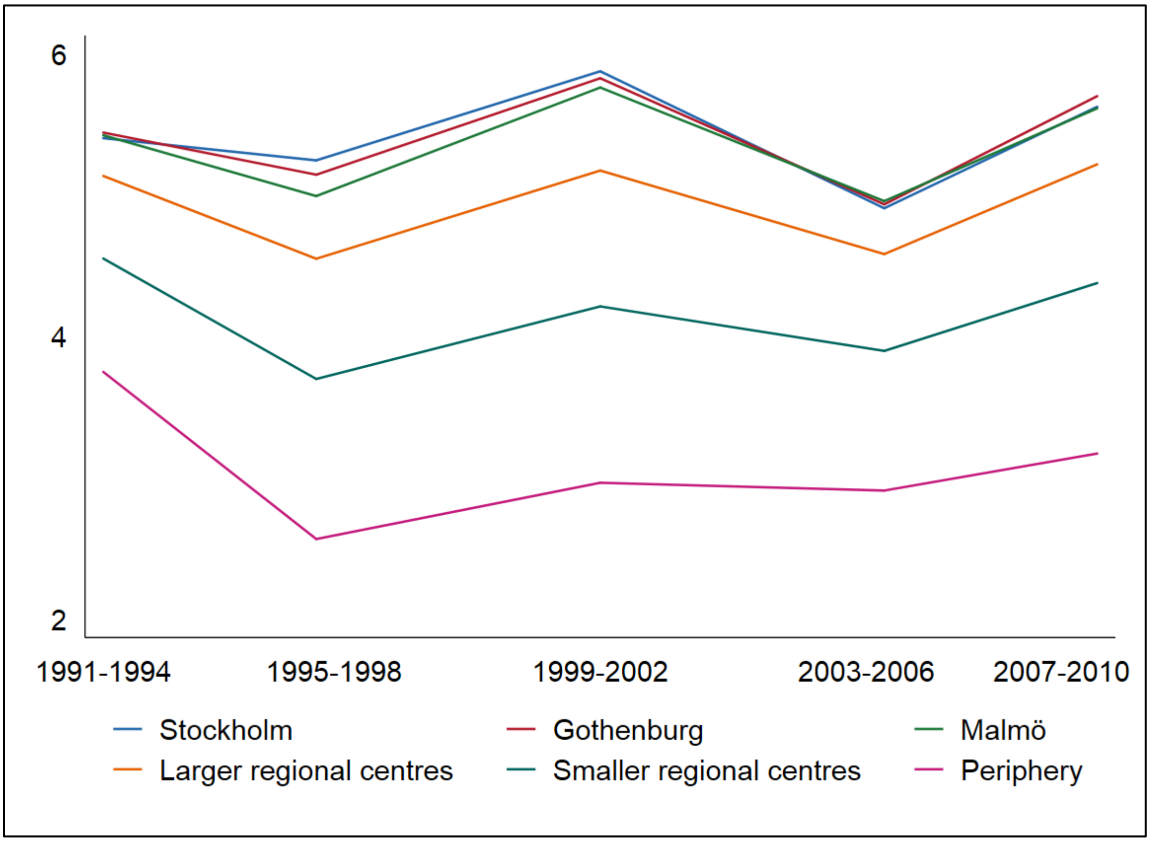


Figure A5. Change in miscellaneous RSR 1991-2010