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Knowledge bases and relatedness: A study of labour mobility in Norwegian regions

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Abstract

Two ideas have emerged as central in evolutionary economic geography in recent years: First, innovation is often the result of meetings between related ideas, and regions are therefore best served by hosting a variety of related industries. Second, innovation often comes from the combination of different knowledge bases. However, there have been few attempts at linking these approaches in empirical studies. This paper connects the dots by examining relatedness among industries with similar and different knowledge bases in specific regional contexts. We focus on regions expected to have different types of innovation systems, from the organisationally thick and diversified RIS of large cities through the more specialised RIS in intermediate cities to the organisationally thin RIS found in small rural regions. The analysis finds that industries with different knowledge bases are related in various regional settings, with combinatorial knowledge base industries having a central role in many regions. However, there are also cases of potential lock-in, where relatedness is mainly found among regions with the same knowledge base.

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Keywords

Relatedness, knowledge bases, labour mobility, innovation, regions

JEL

R12, R23, L52, J62

Introduction

At the time of writing, Bjørn Asheim's most cited paper is his chapter with Meric Gertler in the 2005 *Oxford Handbook of Innovation*, where they introduced the concept of knowledge bases into the geography of innovation literature[1]. They distinguish between industries relying respectively on an analytical and a synthetic knowledge base. A third knowledge base – symbolic – was introduced in subsequent work (Asheim et al. 2007). Analytical knowledge is oriented towards understanding and explaining the world, and innovation requires creating new knowledge. Scientific knowledge is oriented towards problem-solving and mainly relies on novel applications and combinations of existing knowledge. Symbolic knowledge is oriented towards sense-making and creation of cultural meaning (Asheim et al. 2007: 661). The concept of knowledge bases has been central in much of Asheim's work in the subsequent years (e.g. Asheim and Coenen 2005; Asheim and Coenen 2006; Moodysson et al. 2008; Asheim and Hansen 2009; Asheim et al. 2011; Liu et al. 2013; Asheim et al. 2016).

A core idea in recent work on knowledge bases is that different knowledge bases can be usefully combined. For instance, Asheim et al. (2016:9) note that "upgrading can take place through unrelated knowledge base combinations leading to new related industries". Tödtling and Grillitsch (2015) show that firms relying on a combination of different knowledge bases outperform those that are more narrowly based on one type of knowledge. Grillitsch et al. (2016:1) further develop this argument to the regional scale, arguing that "firms benefit most from being located in a region with a balanced mix of all three knowledge bases".

The idea of combining different knowledge bases to create new combinations shares key similarities with another dominant idea in economic geography during the last ten years: the concept of relatedness and the associated literature on related variety. The relatedness literature argues that due to cognitive proximity, knowledge flows and subsequent knowledge combinations occur more frequently across industries that share some basic similarities than across more unrelated industries, but that too much similarity can also hamper the potential for learning (Nooteboom 2000; Frenken et al. 2007; Boschma and Iammarino 2009). Thus, being located in a region with related variety – i.e. with many different, but related, industries – is thought to be beneficial for innovation (Tavassoli and Carbonara 2014; van den Berge and Weterings 2014; Castaldi et al. 2015).

The link between related variety and knowledge bases was already drawn in the so-called ABC paper by Asheim, Boschma and Cooke (2011), forming the basis of the concept "Constructing Regional Advantage". The idea here is that effectiveness of regional policy can improve when taking into account "related variety, which is defined on the basis of shared and complementary knowledge bases and competences" (Asheim et al. 2011: 901). A recent paper by Sedita et al. (2017) combine these concepts in an empirical analysis by interacting relatedness and knowledge base specialisation measures at the regional level. However, few studies have empirically combined the two concepts in the sense of examining the extent to which industries with different knowledge bases are actually related in a regional economic context. Combining knowledge bases with industry relatedness allows us to identify the levels of industrial diversity of regions, how these industries are connected, and what the connecting forces of these industries are. As such, it provides us with another approach to understand the different configurations of regional innovation systems as proposed by Isaksen and Trippl (2016), who made a distinction between organizationally thick and diversified RIS, organizationally thick and specialized RIS, and organizationally thin RIS.

[1] The concept was seemingly first used by Asheim and Mariussen (2003) in a report which is no longer in the public sphere (cited in Manniche et al. 2016).

In this study, we conduct such an analysis in the context of Norway. We develop a measure of the knowledge bases of different Norwegian industries based on the educational background of their workers. Furthermore, we analyse the relatedness across these industries using labour mobility flows, using the concept of skill relatedness and the method developed in Neffke and Henning (2013) and Neffke et al (2017) and applied to Norway by Fitjar and Timmermans (2016). Finally, we examine the composition of industries in a selection of Norwegian regions, focusing on their knowledge bases and the skill relatedness across different industries.

Knowledge bases, relatedness and regional innovation: Review of the literature

Knowledge bases

The concept of knowledge bases was introduced to highlight the very different ways in which innovation processes unfold in different industries. Departing from Laestadius' (1998) distinction between analytical and synthetic knowledge, Asheim and Gertler (2005) describe industrial settings where these two different types of knowledge differ in their relative importance and discuss the characteristics of innovation processes in such settings. Analytical knowledge prevails in science-based industries, where innovation comes from basic and applied research. In industries where this is important, such as biotechnology or information technology, innovation will often be the result of new knowledge of the world. In-house R&D and links to knowledge-producing institutions, such as universities, is therefore essential. In this case, knowledge is often codified and can be transferred over long distances. Nonetheless, firms relying on analytical knowledge tend to locate in close proximity to universities due to the importance of absorptive capacity in decoding the new knowledge developed by basic research. Asheim and Gertler (2005: 298) note the importance of the local "buzz" of such places in sustaining both localised knowledge circulation (Storper and Venables 2003) and labour market opportunities for the creative talent, which this absorptive capacity depends on (Florida 2002).

In industries relying on synthetic knowledge, new applications or combinations of existing knowledge are more important for innovation than the development of completely new knowledge as such. Innovation often occurs as the result of problem-solving, when new solutions are developed in response to problems faced by the firm or posed by customers. These solutions are often not found in R&D, but in well-established knowledge that is applied to new settings. If the innovation process involves formal research, this tends to be mainly in the form of applied research. New knowledge is typically created through processes of trial and error, experimentation, and practical experience. Tacit knowledge therefore tends to be more important in industries with a synthetic knowledge base (Asheim and Gertler 2005).

While the original theory distinguished between these two knowledge bases only, Asheim et al. (2007) added a third: symbolic knowledge. This refers to industries in which aesthetic attributes, symbols, images and narratives are important – in short, the symbolic or sign value of the product. The cultural and creative industries are typical examples of this. In these industries, constant innovation is imperative as products more often compete on attractiveness and novelty than on practical utility (Fitjar and Jøsendal 2016). The knowledge involved is interpretative rather than informational. It also tends to be highly sensitive to local norms, habits and understandings, and therefore highly tacit. This cultural embeddedness of industries with a symbolic knowledge base entails that they will rely on knowledge sources in close geographical proximity, which share the same interpretative schemes (Martin and Moodysson 2011; 2013). However, validation of such interpretations at global nodes of excellence can also be highly important in these industries, underscoring the complex interplay between global and local knowledge also in symbolic industries (Rekers 2016).

A recent strand of research on knowledge bases has focused on its role in regional path development. Asheim et al. (2011) develop the notion of “constructing regional advantage” in which regional innovation policy should be based on an understanding of the dominant knowledge bases of the region’s industries and their associated modes of innovation. Manniche (2012) argues for an integrative approach, where knowledge exchange across different knowledge bases is actively targeted. Following this idea, Asheim et al. (2016) argue that new path development could emerge from combinations of related and unrelated knowledge bases. These perspectives support the idea that fostering less developed knowledge bases in the region could be beneficial for new path development. However, other contributions seem to argue more strongly for policies attuned to the existing knowledge bases in the region. Isaksen and Trippl (2016) talk of analytical and synthetic routes to new path development, showing how new industrial paths in two regions were created by the inflow mainly of one type of knowledge. Martin and Trippl (2014) present a typology of innovation policies for analytical, synthetic and symbolic industries, arguing that policy should provide appropriate support depending on the knowledge bases of regional industries. However, they also note that “this does not imply that regional innovation policies should promote one single knowledge base” (Martin and Trippl 2014:30).

Relatedness

The interest in new path development puts the knowledge base literature in close contact with the literature on related variety, industrial relatedness and, specifically, with the concept of regional branching. Frenken and Boschma (2007) introduced the idea of economic development as a process of diversification through evolutionary branching from the existing regional economic structure. In this perspective, diversification – or new path development – occurs through the recombination of existing technologically related industries in the region to create new industries (Boschma and Frenken 2011). The opportunities for such recombinations depend on the number of related industries present in the region, leading to an interest in measuring and analysing related variety at the regional level (Frenken et al. 2007).

Various studies have demonstrated that higher levels of related variety, due to knowledge spillovers, is conducive to regional employment growth (Frenken et al. 2007; Boschma and Iammarino 2009; Boschma et al. 2013, van Oort et al. 2015). An important question, however, is how relatedness across industries is defined, operationalised, and identified. While theoretical perspectives on relatedness between industries typically draw on the idea of cognitive proximity, i.e. similarities in the ways of thinking (Nooteboom 2000; Boschma 2005), the operationalisation of related variety has traditionally relied on the industrial classification hierarchy.

More recently, researchers started to measure revealed relatedness, which refers to *observed* commonalities of industries based on co-occurrence of activities, similarities in resource use, or connectedness based on trade and human capital flows (Neffke and Henning 2013; Essletzbichler 2015). When co-occurrences, similarities in the use of resources and/or higher levels of connectedness are consistent over a longer period of time, these industries, some of which might appear very different on the surface, may be assumed to rely on similar types of knowledge, skills and technologies. Contrary to measures of related variety, revealed relatedness allows relatedness across industry classes and identifies a more diverse set of related industry pairs. As highlighted by Fitjar and Timmermans (2016), these measures are also better equipped for smaller regions, where the limited number of industries cause related variety measures to underestimate relatedness.

The measures of revealed relatedness have had predictive power in several settings. First, they predict the emergence of new and the decline of incumbent industries. This process of regional branching has been empirically demonstrated on data from Sweden (Neffke et al 2012), Spain

(Boschma et al 2013) and the United States (Essletzbichler, 2015). Consequently, new path development often takes the form of path renewal (Isaksen 2015). Second, regions with higher levels of relatedness can better fend off decline; in other words, they are more resilient to economic shocks (Boschma 2015; Diodato and Weterings 2016). This resilience can be attributed to the ability of related industries to absorb the loss of jobs, as the skills of laid-off workers are valued in related industries. Third, mobility patterns between related industries allow for more efficient knowledge transfers and thus higher levels of innovative performance and productivity growth (Timmermans and Boschma 2014).

Putting the two together

The literatures on related variety and knowledge bases were integrated in the “constructing regional advantage” policy approach (Asheim et al. 2011), and most of the papers on new path development from the knowledge base perspective have built on the relatedness literature (although not the other way around). However, the two perspectives have rarely been integrated in empirical analyses. Sedita et al. (2017) represents an exception. In an analysis of resilience in Italian regions, they explicitly examine the interaction between knowledge bases and related variety in Italian regions, demonstrating that related variety has a positive effect on employment growth and that employment growth is stronger in regions with a large share of synthetic and symbolic (but not analytic) knowledge base industries. Furthermore, there is a significant interaction between related variety and the share of symbolic knowledge base industries, suggesting that symbolic industries are particularly dependent on the existence of related industries in the region.

However, an analysis of related variety and knowledge base intensity at the regional level does not reveal whether regional industries are related to other industries within the same knowledge base or across different knowledge bases. Thus, the potential for “unrelated knowledge base combinations leading to new related industries” (Asheim et al. 2016:9) remains unknown. Knowledge base approaches that rely on worker level characteristics (Asheim and Hansen 2009; Martin 2012; Grillitsch et al. 2015) can be usefully combined with measures of revealed relatedness based on labour mobility patterns between industries (Boschma et al. 2013; Neffke and Henning 2013; Timmermans and Boschma 2014; Fitjar and Timmermans 2016). This allows not only the characterisation of industries based on the extent to which the skills of workers can be classified as analytical, synthetic or symbolic, but also provides indications of how these industries are linked through labour mobility.

We combine the knowledge bases and relatedness perspectives by developing relatedness networks showing the knowledge bases of regional industries. This is helpful in examining whether regional industries are mainly related to other industries with the same knowledge base, or whether there is also significant levels of skill relatedness across different knowledge bases.

This approach allows us to identify: (i) how a particular industry is characterized in terms of (multiple) knowledge bases; (ii) how these industries are related based on labour mobility patterns of workers; and (iii) how the composition of knowledge bases and the level of relatedness differ across regions. The latter provides a supplementary approach to Isaksen and Trippl (2016) and Trippl et al’s (2017) conceptualisation of different regional innovation systems and their associated system failures:

- Organizationally thick and diversified RIS, which are endowed with a variety of industries with different knowledge bases, but which potentially suffer from fragmentation.
- Organizationally thick and specialized RIS, with a more specialized industry structure often relying on similar knowledge bases, running the risk of lock-in.

- Organizationally thin RIS, with few industries and therefore limited opportunities for regional knowledge combinations.

These regions differ in terms of industrial composition, the opportunity for combining different knowledge bases and subsequently the potential for new path development. The approach in this chapter would help to identify whether regions fall in any of the above-mentioned categories, going beyond region size to examine their specific knowledge base and relatedness characteristics in classifying regions.

Measuring knowledge bases and relatedness

The study builds on individual and firm register data from Statistics Norway. Two main registers are used: The register-based employment statistics (regsys) for the years 2008-2011, and the Norwegian educational database (NUDB) up to 2012. We focus on employees with higher education and examine the composition of regions and industries in terms of employees educated in different fields, as well as the labour mobility flows of workers with different educational backgrounds.

Identifying knowledge bases

In order to identify the knowledge bases of different industries, we examine the composition of their workforce in terms of the educational background of employees. This differs from previous large-scale quantitative studies of knowledge bases, which have tended to identify them on the basis of industry codes (Aslesen and Freel 2012), search behaviour as reported in the CIS survey (Herstad et al. 2014; Sedita et al. 2017) or composition of occupations (Asheim and Hansen 2009; Martin 2012; Grillitsch et al. 2015). A shortcoming with the first two approaches is that it tends to classify industries uniquely into one knowledge base, either directly from industry codes or using a more empirically based approach of measuring what information sources are used the most in innovation processes. An important idea in the knowledge bases literature is that firms and industries can usefully combine and integrate different knowledge bases (Manniche 2012). It is therefore preferable to apply measures that allow industries to have more than one knowledge base.

The definition of knowledge bases applied here builds on the knowledge base classification of occupations by Grillitsch et al. (2015). As we do not have access to occupational data, we rely on data on the educational backgrounds of workers. While this might not perfectly reflect the functions performed by each individual worker, we expect that industries relying on a particular type of knowledge would be more inclined to recruit workers educated within this knowledge base. Another issue is that skills of workers without higher education, such as vocationally trained workers, are not considered. However, this might also make it easier to identify industries with particularly high knowledge needs within specific knowledge bases, which require workers educated at a higher level.

For each worker, we consider their highest completed education and, aligned with Grillitsch et al's (2015) occupational classification, classify them into analytical, synthetic or symbolic fields. In all cases, we only consider workers who hold at least a bachelor degree in the relevant field. Subsequently, we calculate the share of workers in each industry holding a degree in an analytical, synthetic or symbolic discipline as a measure of the intensity of this knowledge base in the industry.

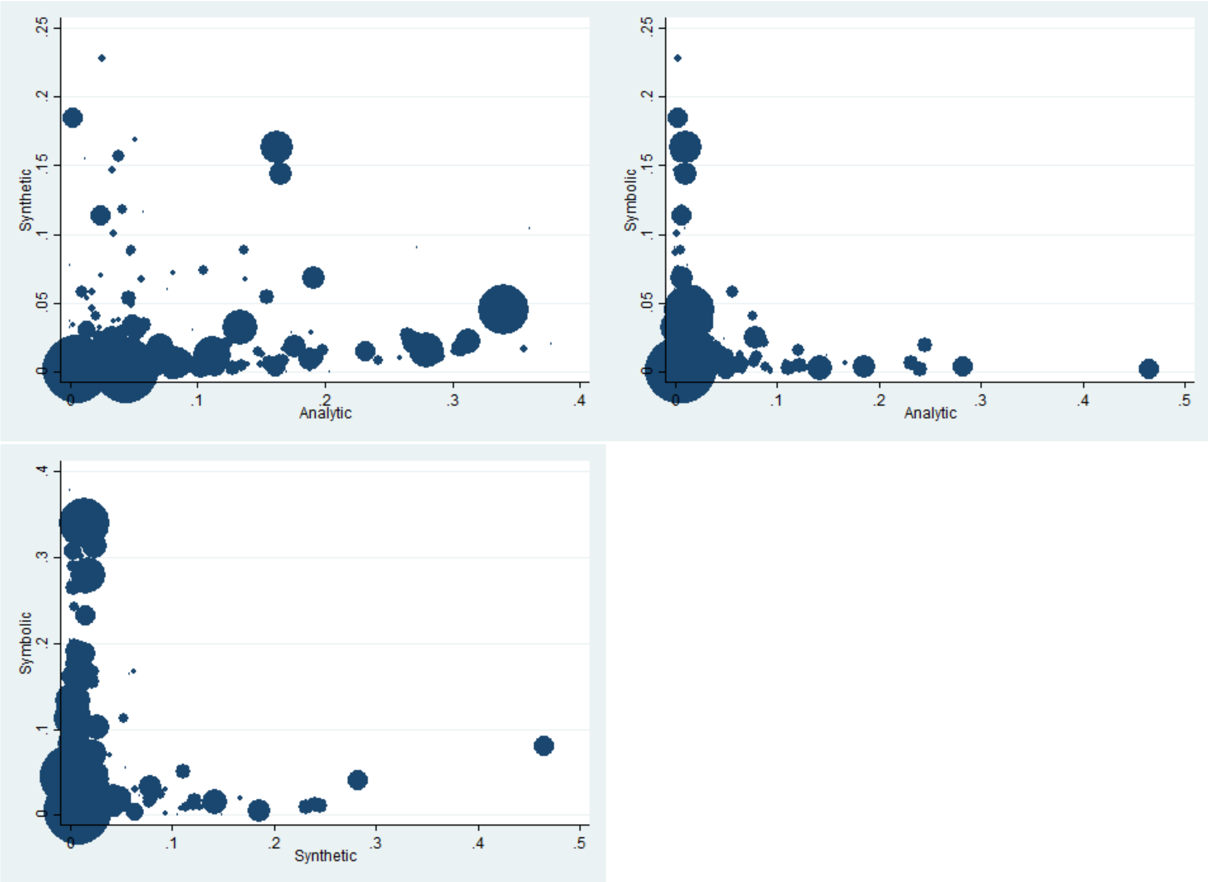
A worker has an analytical education when he or she has a degree in biology, physics/chemistry, mathematics/statistics, geosciences, and pharmacology, as well as those with PhD degrees in IT/computer technology. Synthetic education includes degrees in electrical/mechanical/machine engineering, construction, manufacturing/development, as well as Bachelor or Master degrees in IT/computer technology. Symbolic education covers literature/library studies, historical/philosophical studies, music/dance/drama, arts, media/communication, and architecture.

In total, the educational database lists 786,413 unique individuals with a tertiary level of education by 2012. Among these, 30,072 (3.8 percent) hold a degree in an analytical discipline, 104,112 (13.2 percent) in a synthetic discipline, and 46,487 (5.9 percent) in a symbolic discipline. The majority, 77 percent, hold degrees in disciplines that cannot be classified into one of the three knowledge bases, e.g. in social sciences, health and social work, languages, etc. The share of analytical and synthetic education is higher in the private sector. In total, 26.4 percent of workers in the Norwegian private sector (472,318 workers) held a tertiary level of education in 2011. Of these, 4.1 percent held degrees in analytical disciplines, 16.9 percent in synthetic disciplines, and 5.8 percent in symbolic disciplines.

There is large variation across industries in the share of workers with analytic, synthetic and symbolic educational backgrounds. Considering industries at the NACE four-digit level, 17.0 percent of industries have no workers with analytical education, 8.4 percent have no workers with synthetic education, and 17.5 percent have no workers with symbolic education. At the opposite end of the scale, 22.8 percent of workers in the most analytic-intensive industry have such degrees, whereas 37.8 percent of workers in the most synthetic-intensive industry have synthetic education, and 46.5 percent of workers in the most symbolic-intensive industry have symbolic education. Considering all types of education, only two industries employ no university-educated workers, while 89.6 percent of workers have a university degree in the most education-intensive industry.

Figure 1 shows scatter plots of the 537 NACE four-digit industries considered in this analysis, indicating the share of workers with analytical, synthetic and symbolic education in each industry. The plots are weighted by the number of employees in each industry. Most industries tend to follow the axis of the figure – i.e. they employ few workers within any knowledge base, or they specialise in one knowledge base only. However, the plot for analytical and synthetic also includes some industries with a substantial share of both analytical and synthetic workers. This suggests that the combination of these two knowledge bases is common, supporting the intuition that industries can usefully combine different knowledge bases (Manniche 2012).

Figure 1: Industries by share of workers with education in relevant knowledge base



We further define industries as being characterised by a particular knowledge base if it is within the top quartile of industries by the share of employees educated within disciplines belonging to this knowledge base. For analytical industries, this equates to industries in which more than 1.16 percent of workers are educated in analytical disciplines. For synthetic industries, the cut-off is 4.10 percent, and for symbolic industries it is 1.30 percent. Some industries fall within the top quartile of more than one knowledge base. Table 1 shows the frequency distribution of industries within each possible combination of the three knowledge bases. In total, 44.3 percent of industries are not in the top quartile of any knowledge base and are therefore not classified into any particular knowledge base. The remaining industries are classified into one or, in some cases, several knowledge bases.

Table 1: Knowledge base of Norwegian industries, frequency distribution

	Number of industries	Share of industries, %
No knowledge base	238	44.32
Analytical	56	10.43
Synthetic	63	11.73
Symbolic	90	16.76
Analytical and synthetic	46	8.57
Analytical and symbolic	19	3.54
Synthetic and symbolic	12	2.23
All knowledge bases	13	2.42
Total	537	100.00

Identifying relatedness

To identify the relatedness of different industries (on the NACE four-digit level), we follow the approach as described in Fitjar and Timmermans (2016). However, in this case, we limit the study to consider mobility of educated workers only. Consequently, the skill relatedness measure is estimated on the subset of 465,000-485,000 educated workers employed in the private sector between 2008 and 2011, focusing on the 14 percent of workers that change workplace from one year to the next. Based on the above-mentioned criteria, and following the methodology introduced by Neffke et al (2017) to measure relatedness, we identify 2,714 industry pairs – 13.5 percent of all possible pairs – that are skill related among tertiary educated workers.

We repeat the analysis on the three subsets of workers educated in analytic, synthetic, and symbolic disciplines, respectively. The idea here is to examine whether industries are mainly related because they build on the same skills within one particular knowledge base, or whether they are related across several knowledge bases – i.e. mobility between them tends to be high for workers with different knowledge bases. Table 2 shows the bivariate correlations between the three networks, conducted on an integrated network including all dyads that are connected in at least one of the knowledge bases. This network contains 273 unique industries that are connected to at least one other industry in one of the three relatedness matrices. The analyses show a weak positive and statistically significant (at the 95 percent level based on 500 QAP permutations) correlation between all three networks, indicating that industries that are related for workers in one knowledge base tend only to a marginally larger extent also to be related for workers in the other knowledge bases. This suggests that industries should not necessarily be seen as related for all types of workers – in many cases, they are related mainly within one specific knowledge base, even if there is some overlap.

Table 2: Bivariate network correlations across the three networks

	Synthetic	Symbolic
Analytical	.14	.12
Synthetic		.19

Identifying regions

The definition of regions builds on economic regions as defined by Statistics Norway (2000). We merge economic regions that are part of the same labour market, following Gundersen and Juvkam's (2013) classification of Norwegian municipalities into labour market regions based on commuting patterns. This leaves a population of 78 regions. For the precise definition of these, see Fitjar and Timmermans (2016).

Regions differ in the composition of knowledge bases, as well as in the degree to which regional industries are related (on the latter, see Fitjar and Timmermans 2016). Table 3 shows the five regions with the highest and lowest shares of workers with educational backgrounds within each knowledge base.

Table 3: Knowledge bases in Norwegian regions, share of private sector employment

	Analytical	%	N	Synthetic	%	N	Symbolic	%	N
1	Stavanger	2.01	135053	Kongsberg	14.02	14562	Oslo	2.73	509499
2	Sunndalsøra	1.74	3222	Trondheim	6.98	92319	Lillehammer	2.40	12608
3	Bergen	1.57	150062	Oslo	5.59	509499	Bergen	1.92	150062
4	Skien	1.45	37970	Bergen	4.97	150062	Ørsta	1.80	5676
5	Trondheim	1.43	92319	Ulsteinvik	4.97	10755	Trondheim	1.70	92139
	…			…			…		
74	Hadeland	.23	7381	Brønnøysund	1.34	3444	Setesdal	.34	2332
75	Oppdal	.21	3161	Frøya	1.23	3247	Lyngdal	.34	5849
76	Brekstad	.20	4025	Valdres	1.19	6208	Sandnessjøen	.31	4456
77	Vadsø	.18	3924	Nord-Gudbr.	1.14	6207	Brekstad	.27	4025
78	Risør	.08	2386	Rørvik	1.07	3379	Rørvik	.27	3379

The four largest city regions – Oslo, Bergen, Stavanger, and Trondheim – feature prominently at the top. Each list includes three of the large city regions within the top five by the highest share of employees educated within each knowledge base. Some smaller regions also have high shares of particular types of workers. For analytical knowledge, the peripheral region of Sunndalsøra ranks second only to much larger Stavanger, while the medium-sized city region Skien ranks fourth. Both are highly industrial regions: Sunndalsøra is based around aluminium production, and Skien also specialises in this along with other heavy industry. Notably, Stavanger employs a larger share of workers educated in analytical disciplines than any other region, while not making it into the top five in any of the other two knowledge bases.

Relative to its size, Kongsberg has far more synthetic workers than any other region. Its share of synthetic workers is more than double that of the second-placed region, Trondheim. Kongsberg is a high-tech industrial region with strong specialisations in defence and maritime industries. The other smaller region in the top five, Ulsteinvik, is also a high-tech industrial region specialising in maritime industries. Among the large city regions, Trondheim notably has a higher share of synthetic workers than the other large cities.

The capital region, Oslo, has the highest share of workers educated in symbolic knowledge base disciplines. However, it is followed by much smaller Lillehammer. Another small region, Ørsta, is also among the top five. Both these smaller regions host strong symbolic knowledge educational institutions – the Norwegian film academy in Lillehammer and the journalism school in Ørsta (Volda).

Knowledge bases and relatedness in Norwegian regions

We analyse the regional industrial landscape of selected regions, focusing on the knowledge bases of the industries present in the region and the relatedness between them. Building on Isaksen and Trippl (2016), we examine regions expected to have different types of RIS: Large cities, where organisationally thick and diversified RIS with a wide variety of knowledge bases are expected; intermediate cities, expected to have organisationally thick and specialised RIS, with industries mainly in the same knowledge base; and organisationally thin RIS, with a limited number of industries and weak knowledge bases. For each type of region, we include three different regions: One with a strong endowment of analytical knowledge base workers, one with a high share of synthetic, and one with a high share of symbolic knowledge share workers.

Large cities

Large cities are typically characterised by organisationally thick and diversified RIS. This is reflected in the presence of the largest cities among those with the highest shares of workers within all three knowledge bases. For analytical and synthetic knowledge, all four large cities are among the six regions with the highest shares of workers educated within that knowledge base. For symbolic knowledge, three are in the top five, while Stavanger ranks only 15th. These cities still have somewhat different knowledge base profiles, and three different regions are at the top among the large cities for the three different knowledge bases: Stavanger for analytical knowledge base, Trondheim for synthetic and Oslo for symbolic knowledge.

Figure 2 shows the relatedness maps for these three cities, based on the mobility of all educated workers. In this and subsequent figures, the colours of nodes show the dominant knowledge base in the relevant industry. Red notes denote analytical industries, green nodes denote synthetic industries, and blue nodes denote symbolic industries. Industries that combine more than one knowledge base (i.e. in the top quartile of at least two knowledge bases) are shown in black, while industries with no knowledge base (i.e. not in the top quartile of any knowledge base) are shown in yellow. The edges show relatedness ties across two industries. The nodes are weighted by the number of people employed in the industry.

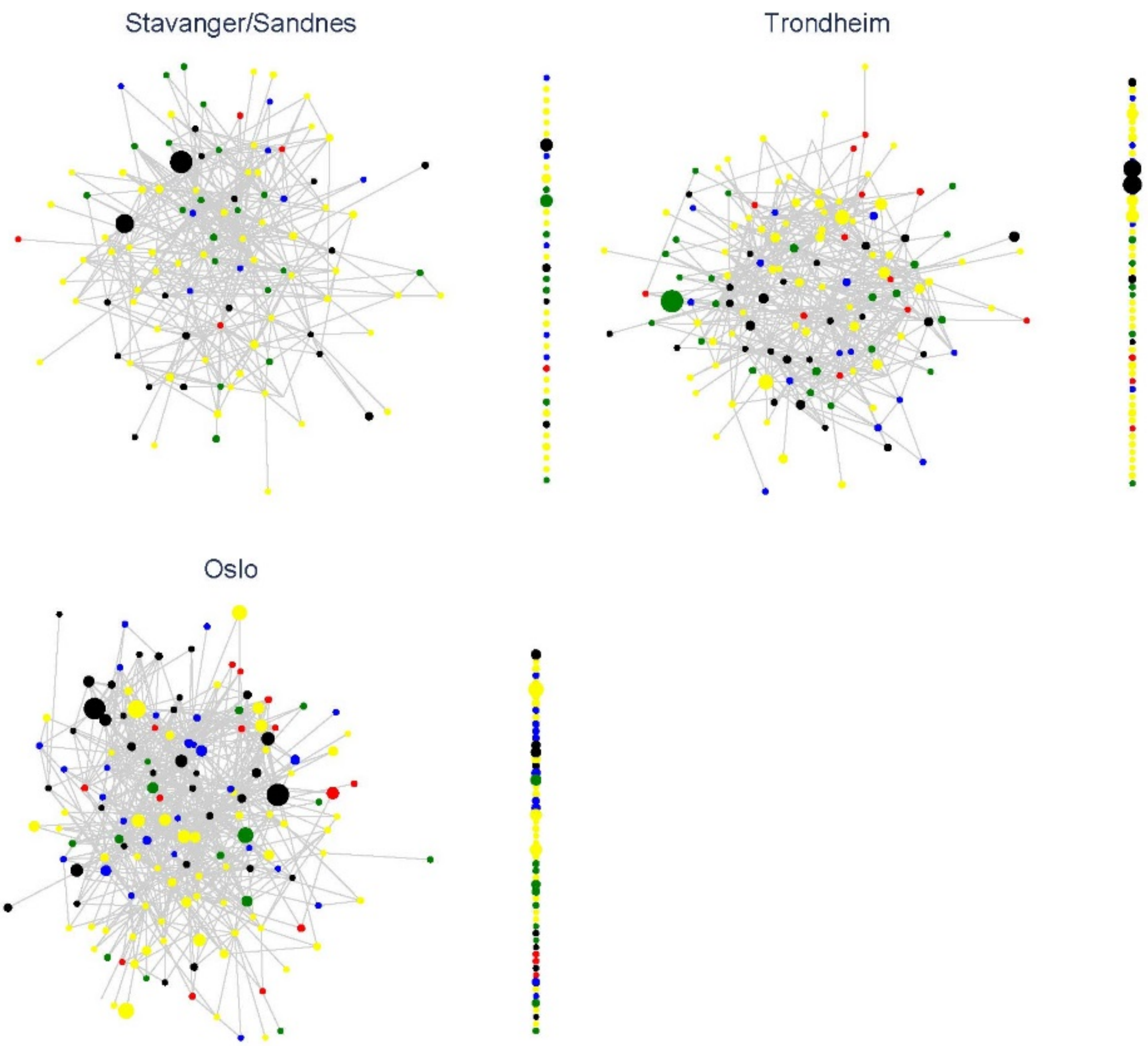
Starting with Stavanger, there are few large purely analytical industries in the region. However, combined knowledge base industries feature quite prominently. In particular, two large combined knowledge base industries dominate the industrial landscape, both part of the city's dominant oil and gas industry. The high share of analytical workers in Stavanger are employed mainly in industries combining analytical with other types of knowledge (mainly synthetic). These industries are furthermore related to several smaller combined, symbolic or synthetic knowledge base industries.

In Trondheim, a large synthetic industry is visible in the map, but the more central positions are occupied mainly by smaller symbolic or combined knowledge base industries. There are also several small analytical knowledge base industries in the map for Trondheim. The region has two large combined knowledge base industries. However, none of these are skill related to any other industries in the region among higher educated workers, and they are thus shown as isolates to the right of the figure.

Various symbolic industries are centrally placed in the relatedness map for Oslo. However, the largest industries in the region tend to be either combined or, in at least one case, synthetic knowledge base industries. The region also have several large analytical knowledge base industries, which are mostly placed in peripheral positions in the network.

Are the large cities characterised by organisationally thick and diversified RIS, with all knowledge bases present? This is most clearly the case in Oslo, where large industries are dispersed throughout the network and relatively evenly sized. Different knowledge bases are represented with combinatorial knowledge base industries among the largest. In Stavanger and Trondheim, the largest nodes are more concentrated in one part of the network, suggesting that these regions are to some extent characterised by specialisation. In Stavanger, symbolic workers and industries are also relatively absent, despite recent efforts to develop creative industries in the region (see e.g. Bergsgard and Vassenden 2011). On the other hand, the region hosts large combinatorial knowledge base industries (mainly linking analytical and synthetic knowledge) with important connections to other industries. In all three regions, several nodes are isolates with no skill-related industries in the region, suggesting that fragmentation might indeed be an issue. In Trondheim, this includes two large combinatorial knowledge base industries. Overall, Oslo is the clearest case of a diversified RIS in Norway, while Stavanger and Trondheim have characteristics of diversified as well as specialised RIS.

Figure 2: Large cities



Intermediate cities

Intermediate cities are often characterised by more specialised RIS, often focusing on one knowledge base. Figure 3 shows the relatedness maps for three intermediate cities, all in Eastern Norway, with strong specialisations in one of the knowledge bases: Skien, Kongsberg and Lillehammer. Skien ranks fourth among the 78 regions in the analytical knowledge base category, fifteenth in synthetic and 27th in symbolic. While there are several analytical knowledge base industries in the relatedness network for Skien, the largest industries tend to be combined knowledge base or, in some cases, synthetic industries. These also occupy central positions in the network, while the purely analytical industries are more peripheral. However, one large synthetic industry is not skill related to other industries in Skien and is shown as an isolate.

Kongsberg has by far the highest share of synthetic knowledge base workers of any Norwegian region. It ranks tenth for analytical and 41st for symbolic knowledge. The industry structure of

Kongsberg is more specialised than that of Skien and Lillehammer, and employment tends to be concentrated in four industries. All of these are combined knowledge base industries and all are related to several other industries in the region. In addition, there are some smaller synthetic industries forming part of this network, with close ties to the larger combined knowledge base industries.

Lillehammer has the second highest share of symbolic knowledge base workers among all Norwegian regions. It has a low share of other knowledge bases, ranking 32nd for analytical and 23rd for synthetic knowledge. Nonetheless, the largest industry in the region has a synthetic knowledge base, and this industry also occupies a central position in the network. There are various symbolic knowledge base industries in Lillehammer, but these are mostly in peripheral positions and not very closely interrelated. The region also has some smaller combined knowledge base industries which are positioned as cutpoints in the network.

While these regions were selected for their strong specialisation in one knowledge base in terms of the share of educated workers, the composition of industries tells a somewhat different story. Although Skien has a high share of analytical workers for its size, its RIS is actually quite diversified, with large industries dispersed throughout the network and many related industries with different knowledge bases. Kongsberg is more specialised, but tends more towards an organisationally thin RIS with few industries present in the network, given that it is so specialised in a few industries. This increases the risk of lock-in. Large combinatorial knowledge base industries are mainly related to much smaller ones specialising in only one of the knowledge bases, reducing the potential for regional knowledge exchange. Lillehammer fits the bill of an organisationally thick and specialised RIS best, again with relatedness mainly between industries with the same knowledge bases. Even in intermediate regions with ostensibly specialised knowledge bases, various types of RIS can thus be found, showing that it is necessary to examine the composition of regional industries closely before drawing conclusions about a region's innovation system and associated system failures.

Figure 3: Intermediate cities

Small regions

Small regions are typically characterised by organisationally thin RIS with limited opportunities for knowledge exchange within the region. While larger city regions tend to be better endowed with highly educated workers, there are nonetheless some smaller and more peripheral regions which also stand out with strong concentrations of workers within particular knowledge bases. One small region makes it into the top five in each of the three knowledge bases: Sunndalsøra for analytical knowledge, Ulsteinvik for synthetic knowledge, and Ørsta for symbolic knowledge, which incidentally are all in Møre og Romsdal. Recent studies by Asheim and Grillitsch (2015), Grillitsch and Asheim (2015) and Asheim et al. (2016) have emphasized that Møre og Romsdal has a prevailing synthetic knowledge base, due to the predominance of knowledge application activities at regional R&D institutions as well as in dominant industries such as the maritime, marine and petroleum industries. At the county level, this is clearly also the case, as the largest cities in the region (Ålesund and Molde) both place higher in the rankings for synthetic than for the other knowledge bases (Ålesund is 12th for synthetic, 41st for analytic, and 18th for symbolic knowledge; Molde is 14th for synthetic, 44th for analytic, and 48th for symbolic knowledge). However, the analysis at the sub-county / labour-market region level shows that Møre og Romsdal also has labour markets with strong endowments of analytical and symbolic knowledge base workers.

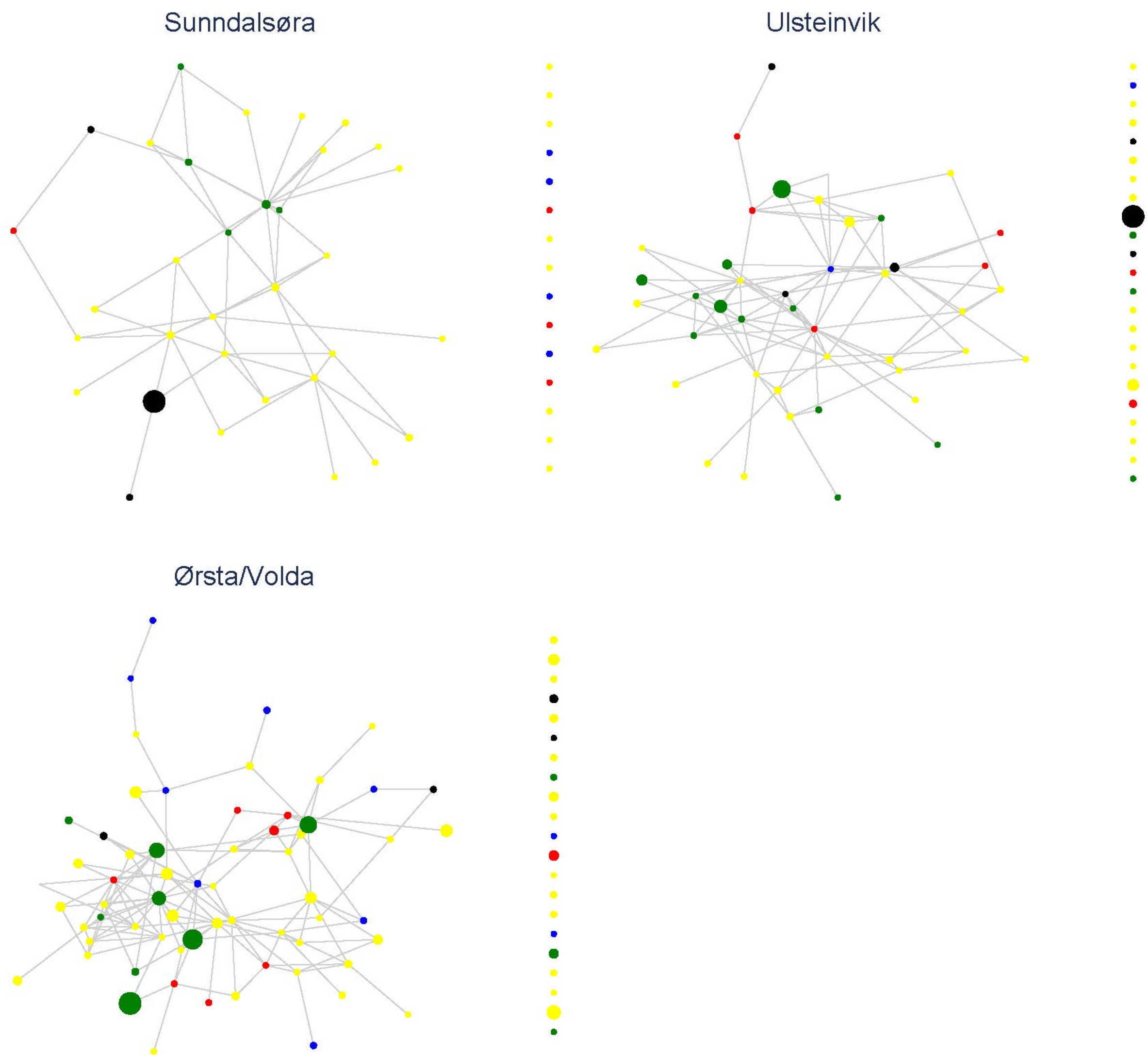
Sunndalsøra has the second highest share of analytical knowledge base workers among Norwegian regions. The region also scores fairly high for synthetic knowledge, ranking 19th, while it is only 66th for symbolic knowledge. This is explained by the largest industry being a combined knowledge base industry which incorporates analytical as well as symbolic knowledge. However, this industry is only related to a few other industries in the region. The most central industries tend not to be intensive in any knowledge base, but there are also some small synthetic knowledge base industries in the network.

Ulsteinvik ranks fifth by share of synthetic knowledge base workers. Its workforce is heavily concentrated in this knowledge base, and it ranks only 49th for analytical and 59th for symbolic knowledge. The largest industries in Ulsteinvik tend also to be synthetic knowledge base industries, and these are also central in the relatedness network. There is also one major combined knowledge base industry, which is not related to other industries in the region and is shown as an isolate. Despite the low level of workers trained in these disciplines, the region also has several small symbolic and analytical industries, sometimes in central positions in the network.

Ørsta has the fourth highest share of workers educated in symbolic knowledge base disciplines among Norwegian regions. The region also has a fair share of synthetic knowledge base workers, ranking 18th, while it is only 62nd in the analytical knowledge base. The relatedness map shows that the major industries in Ørsta are synthetic knowledge base industries. These are interrelated and hold central positions in the network. There are several smaller symbolic knowledge base industries which are dispersed around the network, sometimes in peripheral positions. The region also has several small analytical knowledge base industries in fairly central positions.

The typical small region problems of organisational thinness are to be found in Sunndalsøra, where few and mostly low-skilled industries are present in the network and the region relies on one major industry. Ørsta and Ulsteinvik have more typical traits of organisationally thick and specialised RIS, with network structures not dissimilar to that of Lillehammer, discussed above. In both cases – even in a symbolic region such as Ørsta – this revolves mainly around synthetic industries, although smaller analytical industries also play a role in both regions. The examples also suggest a need to analyse RIS as a disaggregated scale, as different labour markets in the same political region can have very different characteristics and associated needs for policy intervention.

Figure 4: Small regions



Conclusion

A growing literature examines the potential for new path development arising from new combinations of related industries with different knowledge bases. Theoretical contributions (Asheim et al. 2011; Manniche et al. 2016) as well as case studies (Asheim and Grillitsch 2015; Asheim et al. 2016) have illustrated the utility of this approach in individual cases. However, previous research has not combined these two perspectives at a large scale by assessing whether industries with different knowledge bases are related across a large number of regions. This paper conducts such an analysis by combining data on skill relatedness across Norwegian industries and their regional distribution (Fitjar and Timmermans 2016) with measures of the knowledge base composition of such industries.

We examine relatedness across industries with different knowledge bases in regions of different sizes and with different knowledge base specialisations. The analyses show the centrality of combinatorial knowledge base industries across various regional settings. However, synthetic industries are also often central, even in regions which are not necessarily specialised in the synthetic knowledge base. In the Norwegian context, analytical and symbolic industries tend to be small, even in regions with relatively high shares of workers in these knowledge bases. This suggests that such knowledge is often applied in larger synthetic or combinatorial knowledge base industries.

Furthermore, the analyses show that industries are not necessarily related to other industries within the same knowledge base. In some regions, there are blocks of industries with the same knowledge base, but industries with different knowledge bases also often block together and create opportunities for new combinations of related industries with different knowledge bases. This indicates that it is not sufficient to examine the level of relatedness in a regional industry structure to determine the region's potential for knowledge exchange and new path development. It is also necessary to consider whether the related industries have the same or different knowledge bases. Regions with relatedness ties mainly across industries with the same knowledge base could still suffer from lock-in and limited opportunities for new path development, while other regions with less relatedness can nonetheless manage to link industries with different knowledge bases. Conversely, it is also not sufficient to examine the presence of industries with different knowledge bases, as the opportunities for combining these may depend on whether these industries are related or whether they cluster in different parts of the regional industry space. The region does not necessarily benefit from having a balanced mix of different knowledge bases if these are not related.

Furthermore, the distinction between organisationally thick and diversified, organisationally thick and specialised, and organisationally thin RIS do not necessarily follow clear patterns related to the size of the region. Some large cities display tendencies of specialisation with associated risks of lock-in, while intermediate cities – even among those with a high share of workers specialised in one knowledge base – can be quite diversified in the sense of hosting several industries with different knowledge bases, which are nonetheless related. The distinction between organisationally thick and organisationally thin regions also does not neatly follow from region size, as some intermediate cities appear quite thin with limited opportunities for regional knowledge exchange, while smaller peripheral regions can nonetheless host various interrelated industries, often with the same knowledge base.

The analysis comes with several limitations, but also provide opportunities for further research. First, the measure of knowledge bases is based on educated workers only, ignoring the significant knowledge inputs from workers without formal degrees from higher education institutions. This is bound to ignore some important bodies of knowledge, in particular in the synthetic and symbolic knowledge bases. Second, relatedness is measured on mobility patterns only. Some knowledge bases are expected to be related on other parameters; for example through research collaboration in industries that are predominantly analytical. Third, we have not formally analysed the effect of relatedness within and across knowledge bases on innovation or new path development. Therefore, it remains to be analysed whether skill relatedness within or across different knowledge bases is more beneficial. However, this analysis has provided a first stepping-stone towards building such an analysis, and we leave it for future research to follow up on this challenge.

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