Accepted by Progress in Economic Geography, 02.12.2024

This document is the accepted manuscript version of the following article:
Truffer, B., Binz, C., Miörner, J., & Yap, X. S. (2025). Bridging the methodological divide: inspirations from semantic network analysis for (evolutionary) economic geography. Progress in Economic Geography (PEG), 3(1), 100033 (11 pp.).
https://doi.org/10.1016/j.peg.2024.100033

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Bridging the methodological divide

Inspirations from semantic network analysis for (evolutionary) economic geography

Bernhard Truffer[*,**], Christian Binz[*,***,+] Johan Miörner[+,*,+++], Xiao-Shan Yap[**,++]

[*] Eawag, Swiss Federal Institute of Aquatic Science and Technology, Dübendorf, Switzerland
[**] Faculty of Geosciences, Utrecht University, the Netherlands
[***] Geography department, University of Zürich, Switzerland
[+] Department of Human Geography, Lund University, Sweden
[++] EPFL, Swiss Federal Institute of Technology, Lausanne, Switzerland
[+++] CIRCLE, Lund University, Sweden

Abstract

Recent research in evolutionary economic geography addressing radical innovation and grand challenges has advocated for a shift in focus from single technologies and products toward interrelated configurations of technologies and institutions. This suggests moving beyond explaining innovation and industrial dynamics primarily by the existence of appropriate knowledge and capability stocks, to include institutional structures and the ability of actors to shape value-related dynamics. Despite an increasing suite of conceptual and empirical contributions to this extended agenda, its methodological underpinnings have not yet received sufficient attention. A particularly thorny issue is how to bridge quantitative assessments of related knowledge stocks with qualitative process reconstructions of regional development pathways. To bridge the methodological divide, we present a recent approach developed in transition studies – socio-technical configuration analysis and elaborate on how it may inform salient research problems in economic geography.

1. Introduction

Research in evolutionary economic geography has increasingly moved from explaining economic strength of regions and countries in terms of competitiveness and technological leadership towards analyzing conditions for fulfilling broader goals of societal development such as coping with climate change, biodiversity loss, or social justice (see Coenen and Morgan 2020; Tödtling, Trippl, and Desch 2022). The analytical focus thus shifted towards understanding how institutional dynamics and value concerns interact with knowledge and capability-related regional resources to enable regional development and transformations (Jeannerat and Kebir 2016). While this broadened perspective has been advocated by an increasing number of scholars and led to a long suite of conceptual and empirical contributions, the epistemological and methodological ramifications have received much less attention (for some exceptions see Weber and Truffer 2017; Furnari et al. 2021; Balland et al. 2022; Geels 2022; Rutten 2020; Schetter et al. 2024). We will elaborate in this short paper how a configurational[1] methodological approach may provide tools to accomplish this ambition. We aim at contributing to the call of strengthening the methodological rigor and purchase of qualitative process based accounts of regional path dynamics, as advocated for instance by MacKinnon et al. (2019). Additionally, we will show that this approach provides some middle-ground to bridge quantitative and qualitative inroads to evolutionary economic geography.

The starting point is a recently developed methodology – Socio-Technical Configuration Analysis (STCA) – that allows tracking configurations of social and technical elements as expressed in reported statements and actions of different actors in a technological field (Heiberg, Truffer, and Binz 2022). It is part and parcel of the family of semantic network methods that enables the identification of higher order constructs (Truffer 2024). It builds on qualitative content analysis of textual databases and combines it with statistical measures and graphic representation tools from social network analysis. Network representation enables the visualization of the interdependency of statement and action related codes, which can be interpreted as higher order constructs such as socio-technical configurations, institutional logics, or as we will show, techno-institutional resource configurations. This enables the dynamic depiction of shifts in the relative position of competing configurations in a field, and to identify competing actor coalitions supporting or challenging specific innovations or development trajectories. STCA originated in the context of sustainability transition studies to retrace fundamental shifts in socio-technical configurations in specific sectors. An example are emerging decentralized collection and treatment systems of wastewater in cities that compete with the established centralized configurations (Heiberg, Truffer, and Binz 2022).

While transition scholars have demonstrated the explanatory potential of this approach for an increasing number of socio-technical transition phenomena (Heiberg, Truffer, and Binz 2022; Heiberg and Truffer 2022; Miörner et al. 2022; Lesch, Miörner, and Binz 2023; Gong and Truffer 2024; Yap, Heiberg, and Truffer 2023), applications to economic geography problems have remained scant. In the following section, we will introduce the rationale of the STCA methodology as developed in transition studies. The method's application potential to economic geography research will then follow two inroads. A first one relates to the phenomena that evolutionary economic geographers typically want to explain, namely regional path dynamics, or the *explanandum* side of the causal relationship (section 3). The second inroad, elaborated in section 4, turns to the explanatory factors, i.e., the *explanans* side of causality, to explain successful (or not) attempts of regions to develop or attract new technologies or industries. We will conclude by arguing that this approach provides a bridge between the so far widely

[1] We focus here on configurations as higher order constructs composed of technology and institution related elements like story lines, strategies, socio-technical systems - or innovation system, etc. This is not to be confused with configurational approaches to causal explanation following a set-theoretic logic like qualitative comparative analysis (Rutten 2020; Goertz and Mahoney 2012).

separated methodological traditions of qualitative process reconstructions of regional innovation system dynamics and quantitative economic complexity and relatedness studies.

2. Aims and procedures of socio-technical configuration analysis

As originally developed, STCA aims at identifying and measuring configurations of institutional (e.g. values, norms, policies or regulations) and technological (e.g. capabilities, products, or industries) elements in a technological field. Such configurations may be measured by analyzing selected textual document stocks, like newspaper articles, interview transcripts, business reports, meeting protocols, or blog posts. The epistemological assumption is that reports about statements and acts of specific actors will reveal the “deeper structures” that guide these actor’s strategies when having to cope with imminent challenges (see Truffer 2024). A further assumption is that actors cannot combine these elements at will, but that they will typically come in coherent packages, forming identifiable “socio-technical configurations”(Rip and Kemp 1998). As an example, during periods of severe droughts, some actors will promote technological, regulatory and behavioral solutions for solving water scarcity that are congruent with the established paradigm of centralized water infrastructures managed by public authorities and rationalized according to an engineering logic (Heiberg, Truffer, and Binz 2022; Miörner et al. 2022; Fuenfschilling and Truffer 2016). Other actors may prefer more decentralized water technologies, be guided by sustainability concerns and advocate for small scale, user-based management and governance systems (Fuenfschilling and Truffer 2014). STCA enables to identify these alternative socio-technical configurations and track changes in their relative degrees of institutionalization over time (Heiberg, Truffer, and Binz 2022).

STCA builds on earlier approaches for analyzing document stocks. Event analysis (Hekkert et al. 2007) found prominence in the reconstruction of technological innovation system dynamics. It builds on counts of substantive events in a technological field (e.g., investments in particular technologies, opening of new research centers, launching of R&D support programs) as covered in, for example, trade journals. These events are taken as indicators for system building processes whose increasing or decreasing number may indicate processes of maturation or decline of an innovation system (Suurs and Hekkert 2012). A similar approach was introduced to economic geography by Strambach and Pflitsch (2020) in their transition topology framework. The latter is a highly relevant extension to conventional event analysis, as it focuses on sequences of (micro-level) institutional changes that may aggregate and influence broader (macro-level) regional institutional structures. Yet, neither approach explicitly address how socio-technical structures, in the form of configurations of technological and institutional elements, influence actors’ strategies. Discourse network analysis (DNA) responds more directly to this ambition. Established in political sciences (Leifeld and Haunss 2012), it identifies actor coalitions that support or oppose specific policy proposals and the types of arguments that rival camps mobilize in public newspapers to gain political majorities. DNA mostly focuses on discursive statements in policy debates, which reveal actors’ deeply held norms and beliefs, and is primarily interested in tracing shifts in supportive or opposing actor coalitions. STCA instead focuses both on actors’ discursive (public statements) and substantive (reported activities) recorded references to reveal deeper institutional structures that actors mobilize in for preferred technological development trajectories.

Application of the method proceeds in four steps (Miörner et al. 2022): First, a suitable document stock is identified. Most of the hitherto application cases drew on selection of newspaper articles, but also expert interviews, government meeting protocols, project databases, company reports, social media feeds, or other web content have been analyzed (Kriesch and Losacker 2024; Miörner et al. 2022; Lesch, Miörner, and Binz 2023).

In a second step, researchers code text segments in the documents by means of conventional qualitative coding software such as *Nvivo*, *ATLAS.ti* or *MaxQDA*.[2] Individual text passages are coded both regarding the specific actor referred to and the topic (from here on *concept*) the actor is associated with. In STCA, concepts are defined quite broadly, comprising references to technologies, institutions or any kind of resources relevant for the phenomenon studied. Once all articles have been coded, cross-tabulating how often each of the *m* actors has been associated with each of the *n* concepts provides an *nxm* co-occurrence matrix (see figure 1a) that can be graphically represented as a two-mode network linking actors and concepts (see figure 1b).

As a third step, this co-occurrence matrix may be transformed into one-mode networks (figures 2a and 2b) to reveal coherent socio-technical *configurations*. This step requires the calculation of *similarity matrices*, either among actors or among concepts. The similarity between two concepts results from measuring how often actors referred to both concepts conjointly compared to how often any of the two concepts were referred to across all *m* actors. The set of all bilateral concept similarity measures constitutes an *nxn* concept matrix $\boldsymbol{\varphi}$.

One well-established way[3] to calculate similarity measures is the normalized cosine similarity:

$$\varphi_{ij} = \frac{\boldsymbol{X}_i \cdot \boldsymbol{X}_j}{|\boldsymbol{X}_i| \cdot |\boldsymbol{X}_i|}.$$ [4]

Similarity among actors can be calculated in a same way building on vectors $\boldsymbol{Y}_k$ represent a row in table 1a. Entry *k* in this vector lists how often actor *k* has been associated to each of the *n* concepts across the document selection. Two actors *k* and *l* will then be similar to the degree θ_{kl} (sometimes called, "ideationally congruent" [5]) depending on how often they have been related to the same concepts using the same formula as for $\boldsymbol{\varphi}$. Because both one-mode actor *(*$\boldsymbol{\theta}$*)* and concept *(*$\boldsymbol{\phi}$*)* similarity matrices are derived from the same database, they represent dual or mirror projections of these data. Depending on the research interest, either actor or concept similarities may be more informative, or both may be analyzed in conjunction.

Fourth and finally, these similarity matrices can be visually depicted as one-mode concept- (or actor-) networks projected on a two-dimensional plane using network visualization software such as *Visone*.[6] Concepts will result in nodes and similarity values in links. Analysts may then identify interconnected clusters of concepts in specific sub-areas of the plot, which can be interpreted as representing higher-order constructs like socio-technical configurations or techno-institutional resource profiles. Due to our qualitative database, STCA has so far mostly applied visual inspection to identify higher order concepts

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[2] In principle, coding could be done by using large language models or generative AI. However, up to date, these automated coding alternatives lack precision to provide the conceptual differentiation needed for a typical STCA application.

[3] Several similarity measures can be used for this purpose. The most well-known are the Jaccard similarity or the conditional probability based measures that economic complexity studies mostly use (for the reasons to chose one over another see Li and Neffke 2024). Similarities based on co-occurrence counts like the cosine similarity may be biased because the coding strategy may influence how often a certain concept is coded across all documents. This problem can partly be solved by applying the Jaccard similarity, which only considers presence of absence of a co-occurrence. Furthermore, we are applying here symmetrical similarity measures, alternative measures for directed relationships between two concepts or actors can also be used (see Schetter et al. 2024).

[4] $\boldsymbol{X}_i$ represents the vector of concept *i* across all actors listing how many times each actor has been associated with the concept (it corresponds to the i^{th} column in table 1a). $\boldsymbol{X}_i \cdot \boldsymbol{X}_j$ represents the vector product between concept *i* and *j*, i.e. the sum of the products of each actor count for codes *i* and *j*. $|\boldsymbol{X}_i|$ is the length of the vector *i*, i.e. the square root of the sum of all squared actor values in the column. Values of φ_{ij} correspondingly range from *0* (no co-mentioning of the two concepts by any actor) to *1* (the two concepts always mentioned jointly).

[5] See Leifeld and Haunss (2012)

[6] A well-known layout algorithm to accomplish this projection is based on multi-dimensional scaling (Miörner et al. 2022) but a large range of alternatives exist in the network analysis field some of which are available in *Visone*.

(see Truffer 2024). Identification of coherent sub-graphs may however also be based on community detection algorithms established in the networks analysis field (see Javed et al. 2018). Shifts in the relative position and importance of the identified configurations over time may then be interpreted as transitions, maturation, as well as differentiation, splitting or merging of configurations. Corresponding actor networks, in turn, may point at potential actor coalitions that are congruent in their statements and strategies, for instance in pushing a radically novel configuration or defending an incumbent one.

3. Socio-technical reconfigurations: Baden-Württemberg's transition to electric cars

Evolutionary economic geographers are similarly interested in technology development like transition scholars. But more specifically, they focus on how regions may develop or maintain a leading position in providing specific products, services, and their associated industries. Extending STCA to economic geography's typical research questions can be approached from two directions. The more direct application outlined below targets the framing of "objects" of explanation, the *explanandum* of economic geography research, typically innovation-driven emergence or transformation of regional industrial paths. A more indirect way to show STCA's potential contribution lies in its ability to inform the *explanans* side of causation by measuring (regional) techno-institutional resource configurations and how they affect the probability for new industries locating in the region (see section 4).

We will first elaborate how STCA may inform the retracing of regional industrial development pathways. This represents a direct extension of the original application context focused on socio-technical configurations. We will elaborate in the following a step-by-step illustration of the STCA methodology. It elaborates on a recent application of STCA on how the globally leading German region in automobile manufacturing, the federal state of Baden-Württemberg, managed the transition from a century old trajectory building on perfecting the internal combustion engine (ICE) car to a new one focusing on electric mobility (EM) (Gong and Truffer 2024). Regional actors struggled a long time before engaging with the new industrial trajectory, for fear of its massive impact on the well-established regional resource base. In configurational terms, the analysis of this struggle will embrace both socio-technical configurations (alternative technological trajectories) and techno-institutional resource stocks aligned to each of the trajectories.

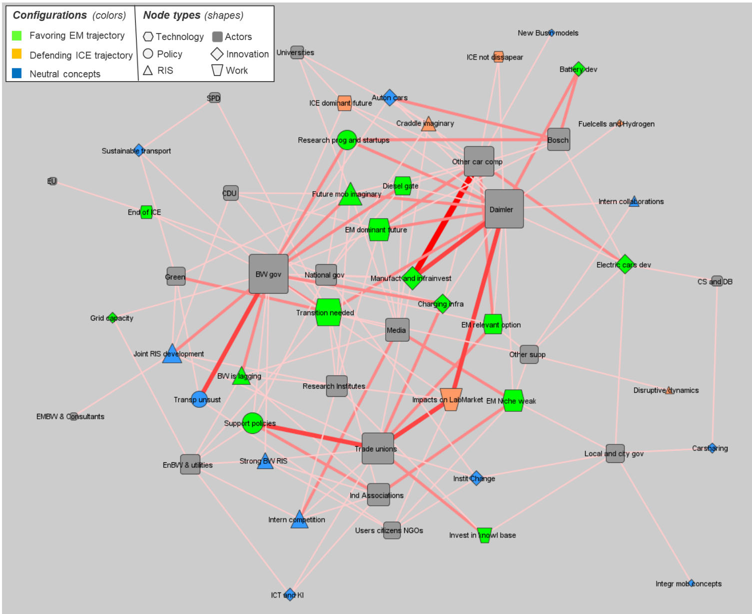
In a first step, we may inspect the co-occurrence matrix resulting from the coding of newspaper articles selected for that purpose.[7] The cut-out of the crosstabulation between actors and concepts represented in figure 1a, indicates how many times each actor code had been associated with a specific concept code in articles between 2015 and 2017. The right-hand side presents the two-mode network of this same data (i.e. color saturation and width of the links are proportional to the number of co-occurrences of an actor and a concept code). The specific time frame was chosen because it depicts the moment when regional actors started pro-actively embracing the EM trajectory. Before, a defensive stance dominated, which built on the view that nothing bad could happen to a global leader in a century old industrial trajectory. A major exogenous event that changed this comforting consensus was the so-called *Dieselgate*[8] scandal. The Dieselgate got wide media coverage in 2015 when the US Environmental Protection Agency accused Volkswagen of having recurrently cheated in CO_2 emissions tests of diesel cars. This led to an immediate collapse of the defensive position of the German automobile industry, which had maintained that climate emissions could be sufficiently cut by continued incremental improvements to the ICE drive train, first focusing on diesel cars, which would later be substituted by e-fuels and hydrogen.

[7] A selection of 170 articles from local and national newspapers between 2010 and 2023 was coded resulting in 21 actor categories and 37 concepts. These codes applied to 517 actor and 795 concept text segments.
[8] Words set in italics represent node labels in the different networks in figures 1-5.

Figure 1b reveals the relations between actors and concepts in this period. The Baden-Württemberg government and the main car manufacturer Daimler are the most often referred actors in the media (*grey squares*). The automobile industry's coverage is strongly related to investment in manufacturing plants and infrastructures for EM (*green diamonds*). Jointly with the trade unions, they pointed at challenges for the regional labor market (*impacts on LabMarket, orange trapezoids*), asking for continued state support for the new trajectory (*support policies)*. The government of Baden-Württemberg questioned the sustainability of an ICE based mobility future (*transp unsust*) by explicitly referring to the *Dieselgate* scandal. In terms of regional resource stocks, they expressed fears that the region had started falling behind its global competitors (*BW is lagging*) and that a new imaginary would be necessary to guide this transformation (*future mob imaginary*).

	Transp unsust	ICE dominant future	EM Niche weak	ICE diss
Media	0	0	2	
AFD	0	0	0	
FDP	0	0	0	
SPD	0	0	0	
CDU	0	0	0	
Green	1	0	0	
Users citizens NGOs	1	0	1	
CS and DB	0	0	0	
Ind Associations	0	0	2	
Trade unions	0	0	0	
EMBW & Consultants	0	0	0	
EnBW & utilities	0	0	0	
Other car comp	0	1	0	
Daimler	0	1	1	
Other supp	0	0	1	
Bosch	0	0	0	
Research Institutes	0	0	0	
Universities	0	1	0	
EU	0	0	0	
National gov	0	0	0	
BW gov	3	1	0	
Local and city gov	0	0	1	

a)



b)

Figure 1: a) Cutout of the actor-concept cross-tabulation for the period 2015-2017. b) Two-mode network of the same database. Colors of nodes represent socio-technical configurations or pathways (green EM, orange ICE, blue neutral). Width and saturation of link color varies with the number of associations between codes. Size of nodes according to the number of times coded. Grey squares represent actors, other shapes concept classes. Layout by stress minimization.

While the two-mode representation provides a direct visual mapping of the co-occurrence matrix, it does not reveal its *configurational* characteristic very well, i.e. dominant or opposing story lines or strategies on which the actors agree or differ. To address this, Figure 2 presents the one-mode *concept* networks, where links between concepts are constituted by their cosine similarity values across different actors. Figure 2b depicts the concept network for 2015-2017 (based on the same data as the two-mode network in figure 1b), and figure 2a the situation three years prior (2012-2014).

How can this be used to identify the techno-institutional characteristics of the opposing technological trajectories and their dynamics? In the earlier period (figure 2a), we see that the ICE supportive orange symbols[9] occupy relatively central positions showing that they were quite dominant in the media coverage. Key arguments were that the costs of a transition to EM would be very high (*impact on LabMarket*) and that the region had weathered many earlier storms because the ICE technology had been invented in the region historically (*cradle imaginary*). The conviction was furthermore that EM still needed a lot of investment before becoming a serious threat to the ICE car (*EM niche weak*). Green nodes referring to the emerging EM trajectory are rather scattered in the figure with the node referring to *EM* being a *relevant option* being quite prominent. However, it is strongly linked to the *weak EM*

[9] Colors were chosen to highlight the institutional and technological elements of the higher order constructs representing two opposing technological trajectories (orange vs. green). The blue nodes refer to regional resource codes and other innovation activities.

niche node, which means that the EM option was mostly mentioned in critical ways pointing at weaknesses that still prevail. Furthermore, we see a rather defensive engagement with all the nodes related to regional innovation system (RIS) structures (*triangles*) scattered across the periphery and not depicting a clear consensus on priorities.

a)

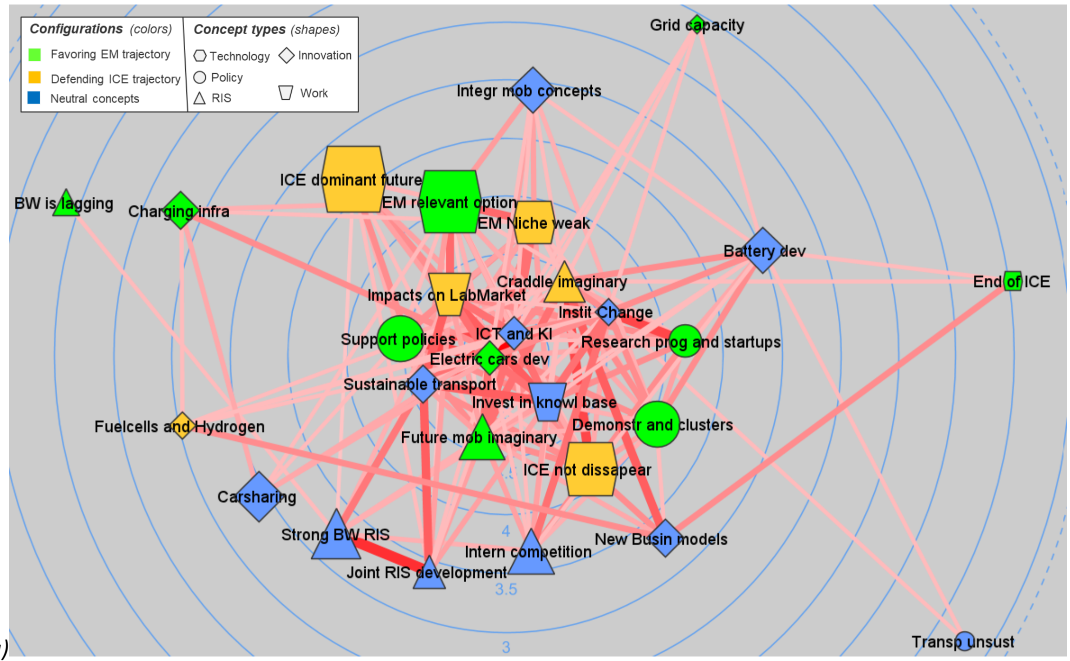


Figure 2a: One mode concept networks 2012-2014: Colors of symbols represent competing trajectories. Size of nodes proportional to the number of times coded, thickness of lines to the cosine similarity value. Layout of elements as centralized-radial (see Miörner et al. (2022) for further explanations).

After the Dieselgate broke (figure 2b), we see the orange nodes moving to the outer rims and green nodes growing and becoming more central. Actual investments in EM infrastructure and manufacturing moved to the center. A new narrative claiming that EM will be the dominant trajectory of the future (*EM dominant future*) emerged in this period as a much more proactive endorsement of the EM trajectory. Also, the claim that a fundamental transition in the production base of the region was needed (*Transition needed*) moved into the center. References to the regional resource base (*blue triangles* to the right) started to get mobilized, most notably, the fear that the region was falling behind its international competitors (*BW is lagging*), such as Tesla and Chinese companies.[10]

[10] In the later phases, we see that these RIS related nodes move even more to the center and become dominant (see Truffer 2024).

b)

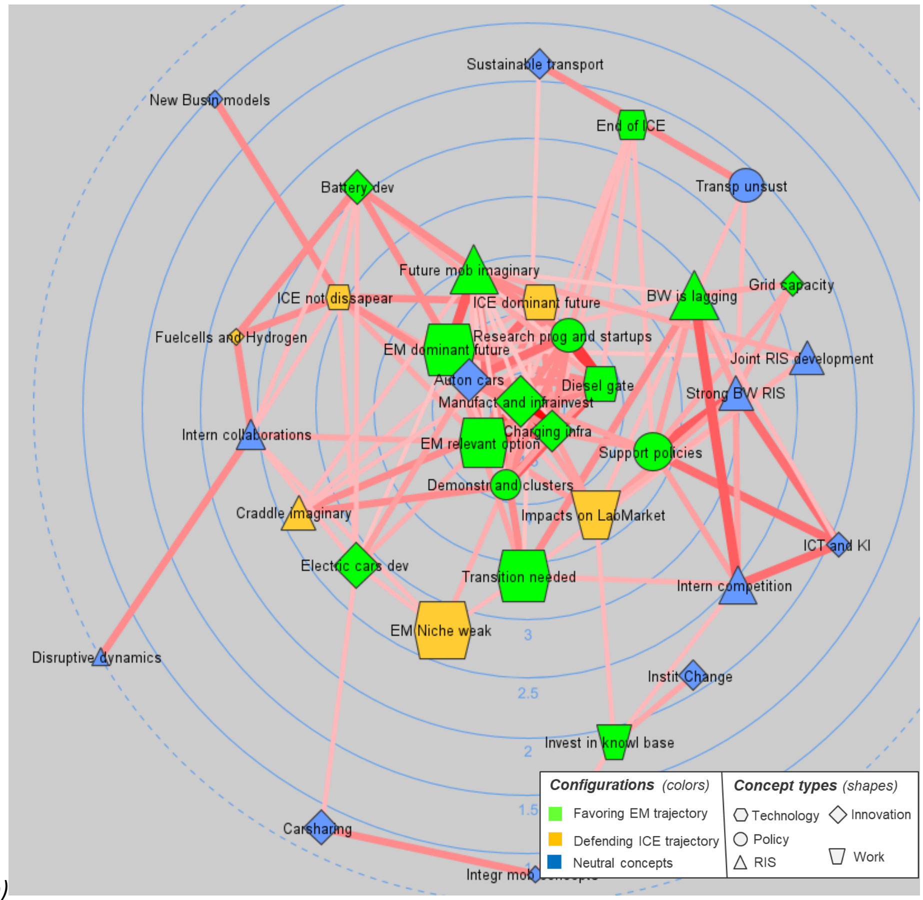


Figure 2b: One mode concept networks 2015-2017: Colors of symbols represent competing trajectories. Size of nodes proportional to the number of times coded, thickness of lines to the cosine similarity value. Layout of elements as centralized-radial (see Miörner et al. (2022) for further explanations).

This illustrative example shows that the basic intuition of retracing socio-technical configurations can easily be extended to the case of techno-institutional resource configurations. STCA may therefore be used in conventional qualitative approaches to reconstruct the path transformation / asset modification dynamics in regional innovation systems in times of struggle over what path to follow (c.f. Baumgartinger-Seiringer, Miörner, and Trippl 2021; Trippl et al. 2020). Put differently, it provides a systematic depiction of technological and industrial elements in their interdependency with institutional factors such as regional imaginaries, calls for targeted investments in the regional knowledge base or the strategic development of the regional innovation system.

4. Techno-institutional resource spaces: explaining regional path development and diversification

If we now turn to the conditions explaining successful regional path development, diversification, and transformation, i.e., the *explanans* side of causality, the basic intuition of the STCA approach will remain productive, pending a few adaptations. From an economic geography point of view, the Baden-Württemberg case is a typical “one region – one industry” case, focusing on how expectations and strategies of different actors struggled with choosing between an established and a partially disruptive future pathway (Tödtling and Trippl 2013; Miörner and Trippl 2019; Binz, Truffer, and Coenen 2016; Gong et al. 2024). However, regions normally host more than one industry and the regional resource base, which enables companies to successfully innovate or branch into new activities, will be shaped by many different factors, including spillover effects, generated by these industries (Frangenheim, Trippl, and Chlebna 2020).

The historically grown industrial resource base in a region consists of a place-specific set of capabilities, which depend on local stocks of codified and tacit knowledge. The region however also needs to develop supportive institutional structures, such as a tailored education systems, R&D networks or supportive policy frameworks (Asheim, Grillitsch, and Trippl 2016), and an 'innovation culture' and adapted value structures, which enable specific industries to grow and prosper (Maskell and Malmberg 1999; MacKinnon et al. 2019; Pfotenhauer, Wentland, and Ruge 2023). A fitting *techno-institutional resource stock* is thus necessary to even consider which kinds of new industries may be attracted to or developed in each region (Trippl et al. 2020; Gong et al. 2024; Frenken, Neffke, and Dam 2023). We argue that such technical and institutional resources also come in specific configurations, which can be analyzed in similar ways as socio-technical configurations. We will first further specify the concept of techno-institutional resource configurations and then elaborate on how these may be analyzed by extended versions of STCA.

4.1 Analyzing regional techno-institutional resource configurations

An impressive stream of research in economic geography has applied a configurational perspective when exploring how cognitively proximate knowledge, skill or capability stocks explain the 'where' of new industry formation (Boschma 2017). Empirical evidence has quickly mounted, highlighting that regions are more likely to diversify into new industrial activities that are related to their pre-existing technological capability stocks. Yet, some development trajectories deviate from this dominant pattern, especially if the new industry has disruptive and new-to-the-world features (ibid.). Recent work argues that even in the case that all capabilities necessary for a particular industrial path are present in a region, territorial institutional conditions may still shape, and ultimately constrain, their constructive combination in path development activities (Frenken, Neffke, and van Dam 2023; Boschma et al. 2017; Carvalho and Vale 2018; Binz, Truffer, and Coenen 2016).

STCA provides a methodological approach for including institutional dynamics in the explanatory model by following a methodological intuition that is closely related to the well-established economic complexity and relatedness literature (Li and Neffke 2024). This literature mobilizes relational data sets, which cross-tabulate for instance export product specializations across countries, skills across manufacturing plants, or technology patents across cities to derive proximity indicators among products, industries, or skills. These can then be visualized as "product spaces" (Hidalgo et al. 2007), "industry spaces" (Neffke and Henning 2013; Neffke, Henning, and Boschma 2011), or "technology spaces" (Boschma, Balland, and Kogler 2015) by using a similar calculus as the one introduced in section 2. The proximity values derived to construct these spaces provide powerful independent variables for explaining the success or failure of regions in developing new economic specializations. In STCA-terminology, these spaces are one-mode concept networks, which mostly focus on knowledge-related elements like technological capabilities or skill sets (Li and Neffke 2024).

A key question is then how this approach could be extended to include institutional dimensions into the explanatory equation. Hidalgo et al. (2007) argue that strengths in specific export products 'reveal' strengths in the resource stock of a country, yet without having to specify what this resource stocks is composed of in the first place. It may encompass technological capabilities, input-output relationships among involved companies, as well as institutional conditions (ibid.). While revealed relatedness measures are a widely-used epistemological strategy, they essentially infer relatedness from patterns of co-occurring product, knowledge or industry specializations, or in other terms the "phenotype" of the underlying causal structures (Schetter et al. 2024). They thus remain rather blurry about what type of relatedness they have in fact quantified (Bathelt and Storper 2023). Very recently Schetter et al. (2024) elaborated how this phenotype approach may be complemented with a "genotype" approach building directly on sets of capabilities that jointly enable places to develop a given industrial activity.

A configurational representation of different forms of proximities between regions in terms of their interrelated technological *and* institutional resources may be aggregated into *techno-institutional* *resource spaces* constituting a natural extension of the existing technology, product, or industry space concepts. We will, in the following, illustrate how these ideas may be approaches by an extended form of STCA.

4.2 Industrial path creation in a single region setting

Starting from a single region perspective, we can assume that the region has established a specific techno-institutional resource configuration, which serves to maintain its strong position for a multitude of existing industries (Steen and Hansen 2018; Grillitsch and Hansen 2019; Martin and Sunley 2014). A typical question is then how this resource base will serve to attract a new industry and how this new arrival will in turn modify the resource configuration of the region. To tackle these questions, we must modify the basic data structures on which STCA is applied. Essentially, we must add new *network layers*. This is because regions do possess these resources often not by 'themselves' but rather as an aggregate of its constituting actors like companies, research organizations, associations, government departments and so on.[11]

To illustrate the basic intuition of a multi-layered configurational approach to techno-institutional resource configurations, we will elaborate on cases with simulated data. Figure 4a depicts a data set of a virtual region composed of ten companies ($A_1 - A_{10}$), [12] which selectively depend on – but also contribute to – specific institutional ($Inst_1$ - $Inst_3$) and technology/knowledge ($Know_1$ - $Know_3$) resources that are key for their continued economic success.[13] Examples of institutional resources could be the availability of specific venture capital services measured on an ordinal scale, or presence of a supportive voter base for environmental regulations. An example for knowledge related resources could be presence of specific skill sets that could be provided by specific teaching programs and on the job training in the companies. Assuming that resource profiles are rather similar within specific industries but may differ between them, we added a layer of binary classification variables to the data structure, which attribute each firm to either an established industry ($OldInd_1$ and $OldInd_2$) or a newly emerging one (*NewInd*). Applying the same similarity calculations as introduced in section 2, we can draw one-mode networks for resources and for industries as depicted in figure 4b and 4c.

The network in figure 4b represents the overall resource configuration of the region, or its techno-institutional resource space. By introducing industries as classification variables, we can show how the different industries (*hexagons*) draw on, depend on, but also contribute to the regional resource stock. We constructed the database in figure 4a in such a way that the new industry depends very strongly on a particular institutional resource ($Inst_3$), which is only weakly present in the region.[14] Figure 4b therefore indicates that $Know_1$ is an attractive locational resource for the new industry, while $Inst_3$ would be crucial, but probably needs further active strengthening to anchor it in the region. Depending on the type of institution needed, this may happen through the implementation of targeted support policies, the immigration of workers with appropriate skill sets, a joint strategy process as in the case of Baden-Württemberg, or other forms of agency targeting the modification of the techno-institutional resource configuration (Trippl et al. 2020).

[11] We assume here and in the following that the techno-institutional resource space can be sufficiently determined by looking at one region exclusively. Of course, substantial resource stocks for the industry located in the region might also be anchored from outside (MacKinnon et al. 2019). We will abstract from these complexities however here and return to the problem of multi-scalar resource flows in the concluding section.

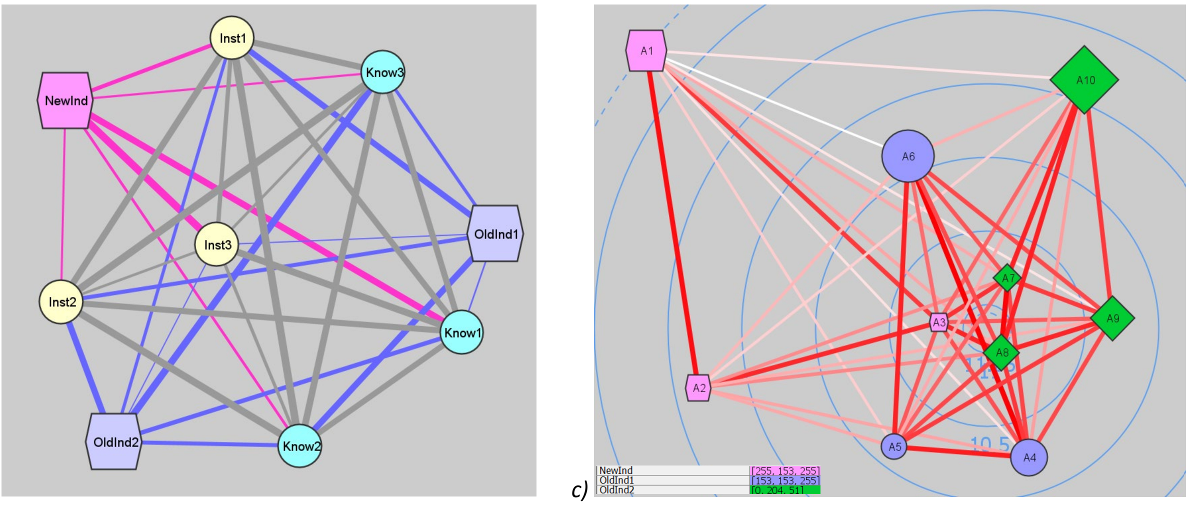
[12] We restrict the type of actors here to companies to keep the example tractable. In general, we could include all sorts of actors like those identified in the Baden-Württemberg case.

[13] Numerical values were randomly attributed between *0* and *9*. However, values of companies were correlated within a specific industry. Values between *0* and *9* may be interpreted as the degree of dependency on and/or the relative contribution of the companies to each resource.

[14] This is represented by high scores of $Inst_3$ for the three companies of the new industry ($A_1 - A_3$), and very low values for the companies in the old industries ($A_4 - A_{10}$).

	NewInd	OldInd1	OldInd2	Know1	Know2	Know3	Inst1	Inst2	Inst3
A1	1	0	0	9	3	2	4	1	8
A2	1	0	0	7	2	2	6	2	6
A3	1	0	0	8	5	4	5	4	3
A4	0	1	0	3	9	4	9	7	0
A5	0	1	0	2	8	5	6	2	1
A6	0	1	0	1	6	3	7	5	0
A7	0	0	1	5	5	6	3	8	2
A8	0	0	1	6	6	7	4	7	1
A9	0	0	1	3	4	9	6	4	0
A10	0	0	1	5	2	8	1	6	0

a)



b) *c)*

Figure 4: Projections of a virtual STCA case depicting the resource profile of companies from three different industries in one region: a) Co-occurrence data table of the virtual example; b) one-mode concept networks with knowledge, institutional and classifying variables ($OldInd_1$, $OldInd_2$, NewInd*); c) One-mode company network with industries as different colors and shapes. Size of nodes represent randomly assumed sizes of the companies.*

The associated one-mode industry network in figure 4c shows how individual companies are positioned in the techno-institutional resource space of the region. Here, industries are identifiable by the color of the nodes. Links between companies indicate the extent to which they draw on the same resources. The companies of the new (*pink*) industry are strongly connected among each other but remain rather peripheral in the regional resource space. The only exception is A_3, which is a small company with stronger similarities to companies A_7 and A_8 from the old industry (*green*). In such a constellation, A_3 might act as an intermediary for the regional anchoring of the new industry.

Extending this line of thinking into time sequences of resource profiles, we will be able to retrace the development of the regional techno-institutional resource space over time and see which industry networks, knowledge stocks or institutional structures have been decisive for embedding the new industry in the region. An empirical illustration for such a systemic resource buildup process is provided by Gong et al. (2024) who analyzed the anchoring of the global EV battery industry in Ningde, China, as resource formation processes between an anchor tenant and regional actors.

4.3 Path creation in a multi-region setting

While the *one-region/multiple-industries* case reported above still lends itself to a process based, qualitative methodological approach, STCA may also inform a more quantitative, variance-based explanation in *multi-region/multi-industries* constellations. In line with complexity- and relatedness studies, the explanatory ambition would be to predict where a new industry is most likely to develop. For the sake of simplicity, we will assume that we analyze a collection of regions, such as federal states in a country, and ask where a burgeoning branch of the AI industry is most likely to emerge. In terms of simulated data (see figure 5a), this means that we must construct a 'global'[15] techno-institutional resource space, consisting of the resources present in the individual regions or countries. To measure the resource configurations of each region, we will limit ourselves to introducing an additional network layer of industries, assuming that resource profiles can more easily be measured at that scale.[16] In order to see how techno-institutional resource configurations at the level of industries and regions match, we need to reorganize the table into two parts where both industries and regions represent the rows, and resources denote the columns of the table (Figure 5b).[17]

Figure 5c shows the corresponding techno-institutional resource space for the six resources in our simulated dataset. Like the one region case in section 4.2, this industry space is not very impressive due to the limited number of variables we chose for the simulation. $Inst_3$ is located at the periphery because we again assume that this resource is key for the new industry, while only being available sparsely in any of the regions.

The one-mode region/industry network in figure 5c now reveals how well the resource profiles of the different regions align with the resource needs of the new industry. As indicated by the width of the pink links, the new industry most congruently fits with the resource profile of region R_4, followed by regions R_1, and R_5 and only weakly with R_2, and R_3. Inspired by the approach by Hidalgo et al. (2007), we may take the similarity measures between the new industry and the different regions as a predictor for where the new industry is most likely to emerge in regression or QCA analyses.[18]

	R0	R1	R2	R3	R4	R5	Know1	Know2	Know3	Inst1	Inst2	Inst3	Total
Ind1	0	1	1	0	0	0	5	0	2	0	2	1	10
Ind2	0	1	0	1	1	0	0	2	8	3	0	0	13
Ind3	0	0	1	1	0	0	9	3	0	0	8	0	20
Ind4	0	0	0	1	1	0	3	0	0	2	7	4	16
Ind5	0	1	0	0	0	0	4	8	2	4	1	0	19
Ind6	0	0	0	0	0	1	6	2	9	8	4	0	29
Ind7	0	0	0	1	0	1	0	5	1	2	9	1	18
NewInd	1	0	0	0	0	0	0	2	6	4	0	9	21
Total	1	3	2	4	2	2	27	22	28	23	31	15	

a)

[15] Global here does not have to coincide with the planetary level, it may relate to any collection of regions, such as the EU with its countries, or federal states in a country like Germany or Switzerland. The actual geographical variation of resource configurations would need further analysis (see Li and Neffke 2024for a more thorough discussion).

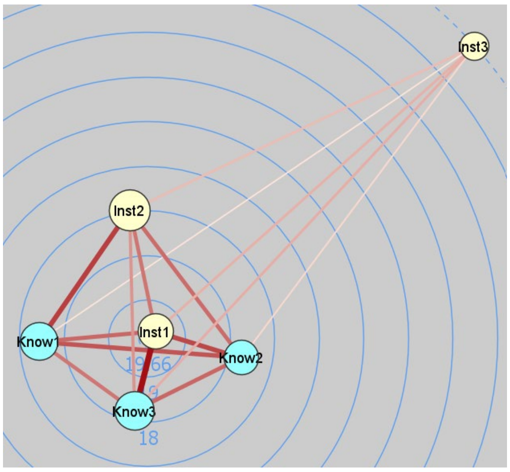
[16] Of course, we could as well start with resource configurations measured at the level of individual companies and aggregate industry profiles from there, like in section 4.2. This would result in a three-layered network structure. For simplicity's sake, we will differentiate only industries and regions. More elaborate on this problem see Schetter et al. (2024)

[17] Resource values of the regions were calculated based on the resource values of its industries assuming that the total value of an industries' resource measures would be proportionally split among the different regions in which it is localized. This way, the total sum of a resource's value across the old industries and across regions adds up to the same amounts (see last two lines in figure 5b).

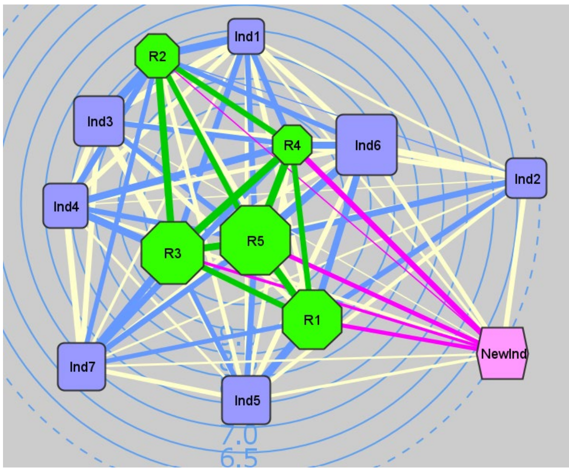
[18] The red framed values in figure 5e represent an equivalent measure to the "density" that Hidalgo et al. (2007) and Boschma, Balland, and Kogler (2014) derived as a predictor for new industry localization.

b)

	Know1	Know2	Know3	Inst1	Inst2	Inst3	Total
Ind1	5	0	2	0	2	1	10
Ind2	0	2	8	3	0	0	13
Ind3	9	3	0	0	8	0	20
Ind4	3	0	0	2	7	4	16
Ind5	4	8	2	4	1	0	19
Ind6	6	2	9	8	4	0	29
Ind7	0	5	1	2	9	1	18
NewInd	0	2	6	4	0	9	21
R1	6.5	8.7	5.7	5.0	2.0	0.5	28
R2	7.0	1.5	1.0	0.0	5.0	0.5	15
R3	6.0	4.7	3.2	3.0	12.0	2.5	31
R4	1.5	0.7	2.7	2.0	3.5	2.0	12
R5	6.0	4.5	9.5	9.0	8.5	0.5	38
Total Old Ind	27	20	22	19	31	6	
Total Regions	27	20	22	19	31	6	



c)



d)

e)

	Ind1	Ind2	Ind3	Ind4	Ind5	Ind6	Ind7	NewInd	R1	R2	R3	R4	R5
Ind1	0	0.312705	0.843005	0.640807	0.443683	0.677408	0.340307	0.307694	0.620038	0.925344	0.715129	0.682996	0.658448
Ind2	0.312705	0	0.055099	0.077421	0.498938	0.803816	0.258438	0.623124	0.662064	0.142396	0.330247	0.595895	0.736906
Ind3	0.843005	0.055099	0	0.757304	0.54524	0.522913	0.662445	0.041308	0.605782	0.984005	0.877036	0.639391	0.630403
Ind4	0.640807	0.077421	0.757304	0	0.304198	0.495161	0.75963	0.425643	0.385367	0.745985	0.886684	0.846787	0.637377
Ind5	0.443683	0.498938	0.54524	0.304198	0	0.659734	0.554731	0.374052	0.95767	0.531235	0.60532	0.511225	0.709489
Ind6	0.677408	0.803816	0.522913	0.495161	0.659734	0	0.473207	0.542356	0.819554	0.592902	0.682642	0.827705	0.963102
Ind7	0.340307	0.258438	0.662445	0.75963	0.554731	0.473207	0	0.266406	0.547777	0.579607	0.896728	0.749752	0.692842
NewInd	0.307694	0.623124	0.041308	0.425643	0.374052	0.542356	0.266406	0	0.48463	0.131015	0.356257	0.675304	0.525326
R1	0.620038	0.662064	0.605782	0.385367	0.95767	0.819554	0.547777	0.48463	0	0.63231	0.68326	0.663639	0.838182
R2	0.925344	0.142396	0.984005	0.745985	0.531235	0.592902	0.579607	0.131015	0.63231	0	0.854988	0.676849	0.662384
R3	0.715129	0.330247	0.877036	0.886684	0.60532	0.682642	0.896728	0.356257	0.68326	0.854988	0	0.890404	0.832721
R4	0.682996	0.595895	0.639391	0.846787	0.511225	0.827705	0.749752	0.675304	0.663639	0.676849	0.890404	0	0.906559
R5	0.658448	0.736906	0.630403	0.637377	0.709489	0.963102	0.692842	0.525326	0.838182	0.662384	0.832721	0.906559	0

Figure 5: Projections of a virtual STCA case depicting resource profiles of different regions in a country. a) Simulated data structure of the example. b) Cross-tabulation of industries/regions with resources. c) One-mode concept networks of the techno-institutional resource space. d) One-mode network with resource profiles of the different regions and industries. e) Cosine distance matrix with proximity values. Colored parts of the matrix correspond to the colors of the links in figure 5d). New industry's fit with regional resource profiles (or densities) are given in the red framed cells.

In terms of dynamics, this approach reveals how new industries anchor in specific regions and then develop over time, while also transforming the corresponding techno-institutional resource space. This approach is close to the established relatedness measures used economic complexity studies. The illustrations elaborated in this section show that the STCA approach provides a versatile framework to address economic geography problems at different levels of aggregation and that it represents a suitable approach for qualitative, process-oriented analyses, which is basically compatible with quantitative multi-region data driven approaches.

5. Connecting socio-technical configurations and techno-institutional resource spaces

The main takeaway of this perspective paper is that recent advances in configurational data analysis represent a very promising addition to the toolbox of economic geographers. Semantic network approaches such as STCA allow a deepened exploration of how interrelated technological and institutional elements create higher order emergent structures like socio-technical and techno-institutional resource configurations, which are decisive for tracing and explaining regional path development, diversification, and transition trajectories. We also outlined how the methodology's basic intuition can be extended to encompass multi-region and multi-industry problems. While we were only able to provide some first pointers for exploring these connections, we see a wide variety of future application options.

A particularly promising perspective is to embark on integrated approaches of techno-institutional resource spaces as an extension of the predominantly knowledge-based approaches in the literature on economic complexity and relatedness. One might be tempted to tackle this problem by simply adding measures for different types of institutional structures to the currently used knowledge-related explanatory variables. However, we would call for some caution with such a strategy. Products, industries and knowledge domains can be represented as rather simple, hierarchical structures, aligning with broadly accepted classification schemes, and which can be retrieved from global public databases (Bathelt and Storper 2023). Institutions are however of a different quality (Martin 2010). First, different institutional dimensions – say educational structures, national approaches to industrial policy making, cultural values or user preferences – will show strong interdependencies, which defy any simple hierarchical classification. Second, we have so far discussed techno-institutional resource profiles as if they represented one integrated predictor for innovation success. We expect that often it will make sense to create separated relatedness measures for knowledge and for different categories of institutions and then analyze the tradeoffs among these (similar to Castaldi and Drivas (2023) or Punt et al. (2022)). Furthermore, the meaning of core institutional terms may vary quite strongly across different regions, making it very challenging to gather standardized global data or derive a 'general' "global" techno-institutional resource space. For instance, one could take voter shares for political parties as a proxy for prevalent societal value orientations in a region. However, the meaning of what a conservative party represents might be quite substantially different in countries like Sweden, Turkey or the US, or even between regions within a country such as Baden-Württemberg or Bavaria in Germany. In consequence, a head-on approach to map global techno-institutional resource spaces through standardized datasets may be confronted with strong conceptual and measurement challenges.

STCA like approaches also suggest new research questions that may extend the realm of economic geography research. First, it will open the field for new empirical cases like the foundational economy, where patenting is not very established, and which provide essential services to citizens. The provision often requires complex socio-technical configurations to be developed and diffused in and across regions. STCA allows for mapping development and diffusion trajectories that deviate from the conventional market- and knowledge-based research focus of the mainstream EEG research. Second, we see a lot of potential for responding to the upcoming call for embracing questions of valuation that become even more relevant in the context of grand societal challenges and which are only partly driven by knowledge competences (Jeannerat 2024). Third, we see a potential for studying "inter-path relations" (Frangenheim, Trippl and Chlebna, 2020; Breul, Hulke, Kalvelage, 2021), which are difficult to grasp from both a conventional qualitative as well as from a quantitative approach. STCA will enable to map inter-path relationships without any a priori assumption of how industries are related. These are just a few examples of exciting future research.

At a methodological level, we see a strong feature of STCA in that it builds on qualitative coding to construct relational and configurational structures, following a systematic and transparent protocol (Miörner et al. 2022). In that sense, it comes with promises to improve the methodological quality of qualitative process reconstructions as demanded for instance by MacKinnon et al. (2019). A distinctive strength of our approach is that the identified higher-order constructs can always be traced back to the original document sources and their underlying qualitative codes and by this suggest further, more focused qualitative analyses like targeted expert interview campaigns or process tracing. We therefore see high potential for STCA to inform qualitative analysis of long-term, cross-regional comparative research questions.

As indicated in this paper, we may however move beyond purely qualitative interpretations and characterize higher-order concepts like socio-technical, or techno-institutional resource configurations, by the standard set of statistical network indicators or algorithms for community detection (Javed et al. 2018). Examples would be to determine key concepts in a configuration by means of centrality measures, where configurational dynamics could be analyzed through changes in these values over time. Such network based statistical indicators may then be used in explanatory models using QCA or provide explanatory variables for more conventional regression models. As STCA can be run with variables of mixed measurement scales be it metric, ordinal, or nominal, constructing resource spaces will not be limited to existing standardized data bases or sets of interview transcripts. This indicates a high bridging potential between qualitative and quantitative methodological approaches.

An admitted limitation of this short paper is that we have not elaborated on the operationalization and measurement challenges related especially to institutional variables. Finding appropriate data will be a definite challenge for configurational methods. An important contribution problem to tackles this problem was recently presented in distinguishing phenotypical form genotypical approaches to measurement by constructing multi-layered network structures as the ones presented in section 4 (Schetter et al. 2024). We introduced layers of classifying (companies to industries) or cross-attributing variables (industries to regions) which enabled us to account for more complex geographical interdependencies like multi-level data aggregation structures, global value chains, complex structured institutional variables or any other crosscutting relationships that may exist among and within actors, concepts, or places. Of particular interest would be addressing multi-scalar resource configurations (Heiberg, Binz, and Truffer 2020), which would require an extended approach like the one we have presented for the multi-region/multi-industries case. Of course, the number of layers and the concept of cross-linkages between these layers requires very serious conceptual and data retrieval effort, which goes beyond what we could elaborate in this present paper. The analysis of multi-layered network structures is one of the current frontier research themes in the general, interdisciplinary network analysis literature (see for instance Boccaletti et al. 2014; Kivelä et al. 2014). We therefore see an exciting new methodological frontier open for economic geographers in the coming years.

Acknowledgements

This paper went through a long gestation process. We would like to thank the members of the Cirus group at Eawag Till Beer, Max Hoos, Djamila Lesch, Meike Löhr and Muhil Nesi for repeated inputs leading to improvements and for feedback from Ron Boschma, Carolina Castaldi, Koen Frenken, Deyu Li, Sebastian Lohsacker and Kerstin Schaefer. We furthermore thank two anonymous reviewers and the editor Michaela Trippl for constructive an inspiring reviews of an earlier version of this paper. Christian Binz acknowledges support from the Swiss National Science foundation project 10001A_215101, and Johan Miörner form the Formas, Swedish Research Council for Sustainable Development grant number 2022-00585. Xiao-Shan Yap acknowledges the European Research Council (ERC) project no. 101117483.

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