Cross-specialization and structural holes: The case of the Dutch Topsectors

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ABSTRACT

In this paper we discuss how an economies' established stronghold industries can form a basis for sustaining competiveness. As changing market circumstances demand industries to stay adaptive, their knowledge bases need to be enriched with knowledge that is uncommon to the industry itself, yet sufficiently familiar for being properly absorbed. Inspired by insights from evolutionary economic geography, we argue why rather than (only) supporting related variety, policy makers should 'cross-specialize' by creating linkages between strong but disparate industries.

We distinguish three forms of cross-specialization, each of them describing how new economic activities can be achieved by converging the knowledge bases of disparate industries. One of the cross-specialization forms pertains to supporting industries at the interface of such unrelated industries. As these cross-over industries consist of parties able to communicate with both of the unrelated specializations, they are an obvious target for policy interventions aimed at closing structural holes in the industry space. Looking at the case of the Dutch Topsectors, we describe how cross-over industries can be identified. We use skill-relatedness and employment data to construct the Dutch industry space, and apply network analytics for calculating cross-over centrality measures. We conclude by discussing research and policy implications.

1. Introduction

Policy makers and economists have since long debated over the question whether or not to support innovation in specific industries. One main argument in favour of 'vertical' innovation policy approach builds on the opportunities offered by local presence of unique resources (Lazzarini, 2015), like specialized knowledge bases and institutions. By referring to modern societies as 'knowledge economies', scholars like Porter (1986) stress that competiveness is derived from the presence of deep and specialist knowledge that is hard to be imitated by others. Assets with such properties particularly occur in scientific and technological domains that have developed into strengths during a long period of knowledge and experience accumulation (Asheim et al., 2011). Government support for the exploitation of this excellent knowledge, so the classical argument goes, is justified by the expectation of additional growth within the specialized industry. Moreover, through local knowledge spill-overs, support for stronghold industries can also spur growth in other industries. The belief that these benefits can exceed the relatively high governance costs of specific policy (as compared to the costs of 'horizontal' innovation policy) motivates policy makers not to stick only to generic interventions.

Frequently used policy options for supporting specific industries, whether they have traditionally been important or recently became excellent, include the development of industry-based innovation programs and cluster policy (Warwick and Nolan, 2014). In practice, implementations of such types of specific policy suffer from various potential weaknesses. The domains in which a country or region decides to specialize are often so numerous, and broadly formulated, that support measures become available to a part of the economy that is arguably larger than the notion of 'specialization' would suggest (Jacobs, 2000). Relatedly, it also has been noted that there is considerable overlap in the domains that regions select (Asheim et al., 2011). Given that the uniqueness of a knowledge base is supposed to provide the competitive advantage, choosing common domains is unlikely to be a successful strategy.

Over the course of the past decade, the debate on policy styles was reinvigorated with insights from evolutionary theorizing. Especially in the context of regional economies, authors have reconsidered the respective advantages of 'backing and picking winners' by fostering established stronghold industries (Lambooy and Boschma, 2001). Although such industries might be competitive in existing business conditions, the question to ask is how success can be sustained over time. The pace with which markets are currently changing demands economies to be adaptive. Therefore, in order to continue capitalizing on the competiveness of historically developed assets, even industries with a stronghold position might have to transform to some extent (Asheim et al., 2011).

The mechanisms behind economic transformation and industrial evolution can be interpreted as processes of knowledge recombination: whether a competitive industry can develop further is largely determined by the availability of knowledge that can enrich the industry's current knowledge base. Since knowledge is most likely to spill over between similar industries, opportunities to exploit and expand idiosyncratic strongholds typically arise from industries with a high degree of technological relatedness (Hidalgo et al., 2007; Frenken et al., 2007). This implies that policy makers should shift their support from the stronghold itself, which is already performing rather well, to adjacent domains that might either strengthen the stronghold or become a stronghold itself.

Even when policy support is aimed at related variety, a pitfall remains. Indeed such a strategy reduces the chance that wrong industries are selected, but recent studies show that true breakthroughs are most likely to stem from recombining notably unrelated types of knowledge (Castaldi et al., 2014). The probability that actors within an economy find original trajectories for sustaining the advantageous position of an industry increases when knowledge from disparate fields is being combined. However, it is also widely acknowledged that knowledge exchange is difficult when parties are cognitively remote (Nooteboom, 2000).

Altogether, there currently is no conclusive answer on the question how to use local strongholds as a basis for diversifying into a competitive economic structure. The current paper contributes to this discussion by introducing a policy approach that aims to address the above-mentioned considerations. In particular, we argue that policy makers should concentrate on the links between strongholds rather than on the strongholds (and related activities) themselves. Although firms from unrelated specializations are unlikely to collaborate, we will stress that policy makers do have means to facilitate this. Essentially, our argument is built on the idea that cognitive distance (and thus technological relatedness) is a malleable rather than a static condition.

The remainder of this paper is structured as follows. First, we argue that the fact that a region can be specialized in multiple unrelated domains provides a basis for forms of knowledge recombination that are unlikely to occur through natural branching processes. Of crucial importance is the claim that certain technological and non-technological developments can bring the knowledge bases of disparate industries closer to each other. Such convergence factors open opportunities for policy makers to bridge strong but seemingly unrelated knowledge domains. This idea of 'cross-specialization' is further elaborated on by discussing three manifestation forms. One of them pertains to supporting industries at the interface of unrelated strongholds. Looking at the case of the Dutch Topsectors, we describe how cross-over industries can be identified. We use skill-relatedness and employment data to construct the Dutch industry space, and apply network analytics for calculating cross-over centrality measures. We conclude by discussing research and policy implications.

2. Economic transformation through knowledge recombination

2.1 Related and unrelated knowledge

Transformation of industrial structures is largely driven by processes of knowledge creation and application. Because knowledge is cumulative and only limitedly transferrable, different regions tend to specialize in different industries. Such excellent industries, which we will call strongholds hereafter, are regarded as a solid basis for regional competitiveness (Warwick and Nolan, 2014). In fact, attention for local strongholds has been rising with the increased interest for cluster policy and smart specialization (European Commission, 2014).

Apart from the earlier mentioned fallacies of specialization policy, there are also other reasons not to concentrate resources too narrowly on local strongholds. Knowledge within a traditionally popular science or technology domain might be highly valuable, but when R&D and economic activity occur in only a very select number of domains there is a risk that a region's knowledge base becomes uniform. Recent studies stress that a more diversified industry composition provides important agglomeration externalities (in addition to the types that are more geographically-bound). These so-called Jacobs's externalities pertain to innovation and growth stemming from knowledge spill-overs between firms or industries with a different knowledge base.

Knowledge spill-overs occur mostly when industries are related to each other. Therefore, scholars stress that innovation demands a substantial degree of technological relatedness. Cognitive distance should not be large (Nooteboom, 2000). Neither, however, should it be too small: when the knowledge bases of two interacting entities overlap almost entirely, there is not much they can learn from each other and resulting knowledge combinations will be hardly novel. Recent research shows that high degrees of related variety within regions can be associated with economic growth (Boschma and Iammarino, 2009), growth in employment (Frenken et al., 2007), and innovation (Boschma et al., 2014). In addition to related variety, one can also distinguish its conceptual counterpart. Unrelated variety is found in conditions in which there are hardly any economic or technological linkages between an economic system's main sectors (Boschma and Frenken, 2011). Instead of looking at similarity amongst firms in subsectors (industries), the degree of unrelated variety is determined by measuring how business activity is distributed over an economy's higher order sectors (see Appendix).

2.2 Recombinant search for breakthrough innovation

In this paper we are interested in the question whether and how the presence of unrelated but specialized knowledge bases can be used as a starting point for strengthening a region's competiveness. Valuable insights on this matter originate in particular from studies on recombinant search. Most of the available studies have been developed in the context of individual firms (Tödtling and Grillitsch, 2014), technologies (Arts and Veugelers, 2014) or even inventors (Kaplan and Vakili, 2014). To a lesser extent, the underlying theories have also been applied for studying an entire industry's 'search' for new product lines or even trajectories (Frenken et al., 2007; Broekel and Brachert, 2014). Given that the key principles of knowledge recombination hold at both the firm-level and at the industry-level, we consider findings on both accounts when developing our arguments.

The pursuit of creating new solutions, like products that could open up new markets, is often interpreted as a search journey. An inherent element of search, as many have noted, is uncertainty. This uncertainty pertains to technological factors ("does it work?") as well as to economic factors ("is there market demand?"). When searching for new opportunities, firms can face various degrees of uncertainty. If the knowledge they are dealing with has already been applied extensively, the familiarity with these 'components' might make it easier to assess how they can be made part of new products: "Recombination usually occurs […] between components that are salient, proximal and available for the inventor" (Fleming, 2001, p. 119). For individual firms, such knowledge is likely to be encountered within the knowledge base of the particular industry it is active in. Reversely, when actors are not familiar with certain knowledge or components, the risk of failure is substantially higher (Fleming, 2001). Experiments with knowledge that has rarely been applied in a certain contexts thus reduce the chance that a firm will introduce a successful new product.

On the one hand, scholars have argued that opportunities for developing breakthrough innovation reside in particular in new combinations of well-used components (Nelson and Winter, 1982; Fleming, 2001). Organizations having a very comprehensive understanding of the state-of-the-art knowledge in a certain domain are believed to be in the best position to encounter and solve weaknesses (Weisberg, 1999). Rather than searching for combinations based on unrelated knowledge, they are advised to capitalize on the 'deep' knowledge base of an industry by exploiting the fact that they are so familiar with this knowledge. The view that organizations at the knowledge frontier have the highest chance of identifying anomalies, in addition to the claim that building on used components is a relatively secure option, makes a case for investing in an economy's strongest industries.

On the other hand, there are also indications that especially the combination of unrelated knowledge holds a breakthrough potential (Weisberg, 1999). The downside of being immerged in one specific knowledge domain is that it goes at the cost of creativity, ultimately resulting in myopia. Therefore, one could expect the most original and radical innovation to stem from combinations of highly diverse knowledge. Next to firm-level studies on bridging unrelated knowledge bases and creating commercially successful ideas, evidence is available for the working of this mechanism at the industry level. As Castaldi et al. (2014) show, the presence of unrelated variety in a region increases the probability that innovative breakthroughs will be produced. Their results imply a trade-off of advantages: more common ground for exchanging knowledge, based on the presence of related variety, seems to be directly at odds with chances of finding truly original knowledge combinations.

The proposed views might seem inconsistent with each other, since they consider relying on either related or unrelated knowledge recombination to be the most promising way for identifying radically novel propositions. Kaplan and Vakili (2014), using patent data, provide evidence for the claim that the presumed trade-off may in fact be a matter of a 'double-edged sword' (Sternberg and O'Hara, 1999). The merit of combining input from the same deep knowledge base is a higher level of novelty, but combining unrelated knowledge is associated with more economic value. Recently also Arts and Veugelers (2014) have shown that combining formerly uncombined but familiar technology

components forms a solid basis for breakthrough innovation. The finding that recombining deep knowledge and recombining unrelated knowledge each have their own respective benefits holds important implications for innovation policy, as it calls into question whether there are perhaps any synergies to exploit also at the level of industries (rather than technologies).

2.3 The potential of cross-industry linkages

So far, the debate on related and unrelated knowledge has focused mainly on identifying optimal levels of (un)relatedness, thereby neglecting any other properties of the knowledge that is involved. A particularly relevant issue, in our view, is the question what kind of unrelated knowledge is being combined when searching for breakthroughs. For an individual firm, having its own unique experiences and thus facing an idiosyncratic search space, all knowledge that is unfamiliar might be considered as unused. This does not hold at the level of the entire economic system. Here, the question whether a component is used depends on how much it has been applied in general, by any of the actors that is part of the system. It is very well possible that economic systems contain multiple specializations, each of them relying on a couple of highly related and extensively used knowledge bases that are not necessarily also linked to the strong knowledge bases of other specializations. This situation is also sketched in Appendix A.

Based on arguments for the respective benefits of the two types of knowledge recombination, we would expect that particularly promising opportunities arise when deep knowledge from one specialization is combined with deep knowledge from another specialization (Fleming, 2001). Arguably, the sophisticated knowledge within excellent industries has been used extensively, and is therefore more promising than knowledge from a random industry. However, because a firm from one stronghold will consider the knowledge from another (unrelated) stronghold as unfamiliar, it is unlikely that the firm will indeed make combinations of components that would be classified as 'used' at the system level.

The rich potential of recombinant search we envisage requires knowledge to flow between very dissimilar industries. Previous studies have shown that this is relatively uncommon. Due to for instance a large degree of cognitive distance, knowledge flows remain absent even if actors are close with respect to other forms of proximity (Nooteboom, 2000).

One possible and probably overly deterministic conclusion would be that efforts to combine disparate knowledge bases are likely to be in vain. Another view at it this issue, however, is that policy intervention is particularly relevant in situations in which knowledge flows can be fruitful but will not naturally emerge. The policy challenge when facing such kind of system failure, falling under the header of information asymmetry, is to enable these 'unnatural' knowledge flows.

2.4 The evolution of relatedness: branching and convergence

According to Boschma and Frenken (2011, p. 64), "the sectoral composition of a regional economy at one moment in time provides and constrains (though does not determine) diversification opportunities of regions in the future". Existing discussions on regional specialization and diversification have particularly looked at branching mechanisms: the evolutionary processes through which economic activity shifts to technologies and industries that are related to the existing ones. As a result of innovation, path dependent knowledge accumulation and creative destruction, old industries diverge into industries that draw upon a more specialized knowledge base. On this basis one might expect that new branches are more different from each other than those closer to the 'stem' of

knowledge accumulation[1]. Yet, in modern economies, we also observe various trends that might increase the extent to which different industries share similar knowledge.

Attention for cross-industry similarities typically concerns technological factors, as also expressed by Neffke et al.'s call for more research on role of generic technologies (2011). Perhaps the most pervasive development of modern times is the on-going adoption of a general purpose technology (GPT) like ICT (Bresnahan and Trajtenberg, 1995). The rise of telephony, computers and internet has led to drastic changes in the production modes and business models of firms in virtually every industry. Although those developments resulted in the rise of many new sorts of business activities, actors within both old and new industries now share a body of ICT-related knowledge and skills. This effect of convergence is inherently connected to the nature of any GPT.

Apart from ICT, the European Commission believes the following generic technologies (also referred to as key-enabling technologies; KETs) to be crucial for the competiveness of industries in the knowledge economy: nanotechnology, micro- and nano-electronics including semiconductors, advanced material, (industrial) biotechnology, photonics, and advanced manufacturing technologies. Coining the notion of smart specialization, Foray et al. (2009) urged policy makers to enrich local strongholds by adopting such new multi-purpose technologies. By following the smart specialization approach, regions that will not lead in the development of new technologies can at least take the lead in specific applications of these technologies. Of course, this does presume that the regions have a sufficient level of absorptive capacity for actually staying up to date with respect to relevant technological developments.

In addition to developments pertaining to 'technology' in the narrow meaning of the word, also the increasing importance of services makes (or could make) the knowledge bases of industries converge. As manufacturing firms started realizing they can only beat the commodity trap by switching to the delivery of customer-specific solutions and experiences, many of them now focus on service-based business models (Chesbrough, 2011). Both the challenges of 'servitization' as well as the actual business models are factors with relevance for firms from a high variety of industries (Olivia and Kallenberg, 2003).

3. Cross-specialization

3.1 Cross-specialization logic

In the previous sections, we provided theoretical reasons for why combining used but unrelated components might result in the identification of fruitful trajectories. A promising but so far largely overlooked way to avert the treat of other regions specializing in the same domain is by searching synergies between multiple deep and region-specific knowledge bases. Since actors from distinct specializations possess knowledge bases with little overlap, finding complementarities and establishing partnerships might be difficult and thus rare. Our solution for solving this is to find ways to create cross-overs between present specializations. This is the core idea of cross-specialization. Rather than advising policy makers to concentrate their resources (only) on individual strongholds, and economic activities most related to those, we suggest they should search for ways to enable knowledge transfer crossing those strongholds.

With our discussion of convergence factors, we aimed to argue that relatedness indeed is malleable (Asheim et al., 2011). Ultimately, relatedness is a matter of perception.[2] If firms realize that they are in fact (to a certain extent) similar to firms in other industries, they might be willing to learn from each other or with each other (Nooteboom, 2000). It is these kinds of interactions that then form

[1] This does not necessarily imply that regions only diversify: due to relatedness, the new branches are still relatively similar to the industries from which they originate. Neffke et al (2011) demonstrate that relatedness in a region can remain stable when entry of dissimilar industries and exit of dissimilar industries equal each other out.

[2] Since perceived relatedness is hard to gauge, most of the available empirical measures actually concern *revealed* indications of relatedness (Neffke & Henning, 2008).

the basis for more intensive knowledge exchange, possibly resulting in original and even breakthrough knowledge recombination (Castaldi et al., 2014).

When convergence factors do not simply happen, but can actually be actively influenced, policy makers in the end do seem to have possibilities for using local strongholds as a basis for developing a competitive industrial structure. Essential is the identification of a body of knowledge that is potentially relevant for, but not actually shared yet by unrelated industries. Such knowledge can be used to encourage unrelated firms to engage in mutual learning and joint experimentation.

3.2 Forms of cross-specialization

The working of cross-specialization is best to be explained by considering three possible mechanisms through which exchanging unrelated but valuable knowledge can result in economic diversification (the dark grey parts of Figure 1). In short, recombining knowledge from stronghold industries can lead to innovations that are an extension of what is already being offered within an industry (A), that are entirely novel within an economic structure (B), or that contribute to (and benefit from) developments in system-level topics and technologies with a horizontal nature (C).

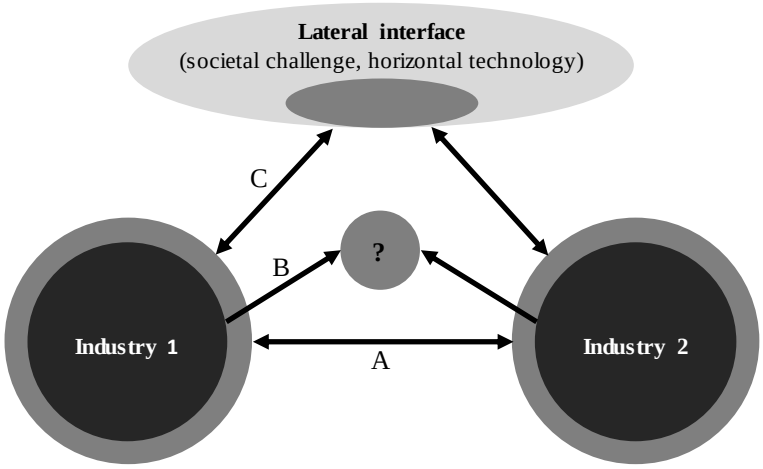


Figure 1: Three forms of cross-specialization

A. Direct knowledge exchange leading to related products

One possible result of combining unrelated knowledge is that firms develop products or services that are similar to the kind that at least one of them was already providing. This situation would occur when knowledge of one industry is introduced in the context of another industry, and used for diversification into products that are related to the existing portfolio of at least of these industries. By drawing on a body of knowledge that was accumulated with time and experience, conform the idea of recombining used components for which deep knowledge is available (Fleming, 2001; Kaplan and Vakili, 2014), these new branches might be more promising than branches originating from other input.

Examples of this scenario include situations in which (specific) technologies or knowledge developed for a certain market were adopted and applied by an entirely different. For instance, specializations in the fields of robotics, chemicals or materials have a large potential for being applied in other possible stronghold domains, like agriculture or health. Firms that only search for new solutions by starting from what they do themselves might fail to identify complementarities with industries that are at first sight unrelated. Actors outside an industry boundary, like public authorities, sometimes have more overview and are better positioned for observing promising cross-overs.

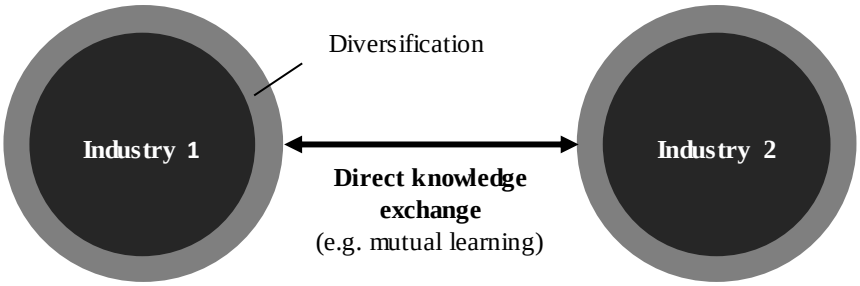


Figure 2: Cross-specialization type A: Diversification through direct knowledge exchange

B. Direct knowledge exchange leading to relatively unrelated products

A second form of cross-specialization concerns the (externally facilitated) interaction between actors from two industries, leading to the emergence of a niche that is relatively distant to the original products of both industries. While cross-specialization type A corresponds mostly with diversification based on solving anomalies within stronghold industries, type B fits more with the other side of the double-edged sword of knowledge recombination (Kaplan and Vakili, 2014). That is, this form is based on the finding that especially recombining knowledge from unrelated industries lies at the root of breakthrough innovations that are radically novel for all parties involved (Castaldi et al., 2014).

As observed in the evolution of many industries, the initial emergence and subsequent maturation of niches is highly determined by the types of knowledge that are present in established markets (Klepper, 2002; Agarwal et al., 2004). A well-known example is found in the onset of the automobile industry. Amongst the first firms to successfully enter this market were the ones having capabilities and knowledge stemming from industries like coach and bicycle manufacturing (Boschma and Wenting, 2007). For firms in either industry, making automobiles was something really different from developing yet another line of coaches or cycles. It is the recombination of such distinct specializations that can result in product lines lying beyond those that would be developed in regular branching processes. Another, less technical example is the recent rise of business activities like 'search engine optimization' services, which is probably most remote to being a mix of website development and branding consultancy.

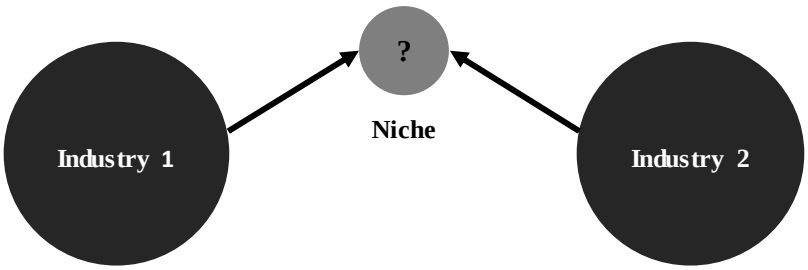


Figure 3: Cross-specialization type B: Niche creation emerging from direct knowledge exchange

C. Indirect linkages based on societal challenges / horizontal technologies

Apart from relying on direct interactions between actors from unrelated industries, knowledge exchange can also flow through inherently lateral interfaces connecting multiple specialized knowledge bases. This form of cross-specialization is somewhat congruent with the platform approach suggested by Asheim et al. (2011), be it that we are particularly interested in joining up unrelated rather than related knowledge domains. We distinguish two varieties of lateral interfaces: societal or system-level challenges (i.e. the *demand* for solutions), and horizontal technologies (i.e. the *supply* of technological opportunities).

Even when engaged in only economic or innovation affairs, most of the issues policy makers are facing are not orderly related to distinct industries. Rather, policy reality consists of challenges that occur at the level of the entire economic system. These challenges can concern, for instance, issues like education, unemployment, entrepreneurship, or environment. With the launch of the European framework programme Horizon2020, European innovation policy is increasingly being oriented towards societal challenges of a complex nature. Problems related to health, energy or climate demand solutions in which a wide variety of disciplines is involved. The resulting fact that system-level themes stretch over a broad range of industries implies that there are ample opportunities for actors from disparate industries to interact with each other. A topic like health might involve firms from industries as different as robotics, chemicals, web-solutions, and so forth. Whereas a regular branching process might lead those firms to pursue their idiosyncratic trajectories, being involved in fighting societal challenges can expose them to knowledge from domains they would otherwise never look at. The cross-specialization that thereby could occur is arguably more indirect than the types emerging from mutual learning (like in type A and B).

The second type of lateral interface is formed by horizontal technologies. In section 1 of this paper we already introduced the idea that generic technologies like GPTs are regarded as factors that might lead the knowledge bases of unrelated industries to converge. Equally interesting are the kind of research facilities that are of relevance for the development of knowledge that can be applied in very different contexts. This can range from facilities for very fundamental research, to laboratories for testing new materials and applications for 3D-printing. The latter is in fact an example of a research facility for something which might become a general purpose technology, since 3D-printing is already being used for fabrication of medical implants, houses, and even weapons.

Just like in case of the broad societal themes, horizontal technologies mark a possibility to unite actors from different knowledge domains. Rather than contributing knowledge for creating solutions to grand challenges, the focus of parties involved now typically lies on the shared wish to develop and especially utilize the opportunities of these technologies (Gambardella and McGahan, 2010). For a topic like advanced imagery, for instance, one can easily imagine a scenario where firms from very different spheres enjoy the benefits of jointly investing in facilities like microscopes and corresponding software. Again, learning effects can occur at various sides. Experience with using these facilities for various purposes can in the first place lead to improvements in the hard- or software. Secondly, and more interestingly, the fact that parties from diverse spheres interact with each other increases the chance that they learn from each other's experiences with the technology, or any other knowledge that might flow once linkages are established (Asheim et al., 2011).

Essentially, this last type of cross-specialization can be regarded as a variation on smart specialization (Foray et al., 2009). The core idea of smart specialization is to use GPTs for revitalizing industries in which a region has traditionally been excelling. A famous example is the use of nanotechnology in the Finnish pulp and paper industry (Foray et al., 2009). The kind of specialization that is envisaged here goes one step further, since the focus is at using generic technologies not only for boosting traditional industries (individually), but also for linking them to each other.

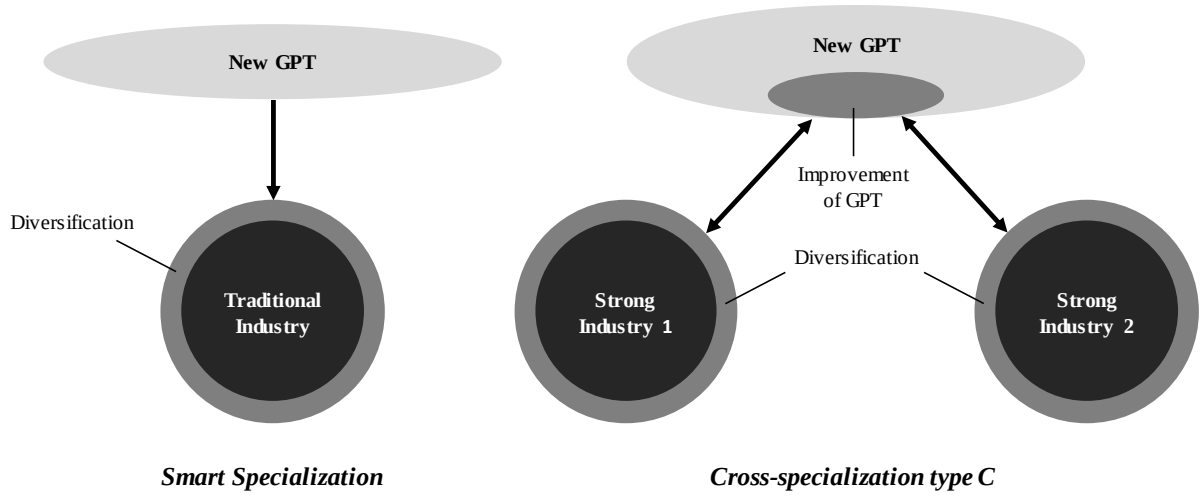


Figure 4: Cross-specialization type C (knowledge recombination through indirect linkages) as opposed to smart specialization.

4. Cross-specialization as a matter of targeting structural holes: empirical illustration

4.1 Identification of cross-over industries

Cross-specialization is a matter of creating interfaces between disparate knowledge bases. Some knowledge bases contain components that have been used already in a wide variety of applications (Fleming, 2001). Such knowledge bases form unique assets for the current competiveness of an economy, but not necessarily for the future. Our suggestion is to identify promising forms of economic transformation consists of offering policy support for facilitating the recombination of used but (so far) unrelated components.

The technological relatedness of industries can be represented as a network. The nodes in the conceptual figure below refer to industries: a bigger node implies that an industry is performing better (economically and/or scientifically). The strength of the ties signals how related two industries are. Relatedness is usually measured by looking at trade-flows or co-citation in patents. Existing studies often focuses on identifying optimal cognitive distance (e.g. closeness centrality, Neffke et al., 2011). Rarely, to our knowledge, do they take into account the economic significance of an industry.

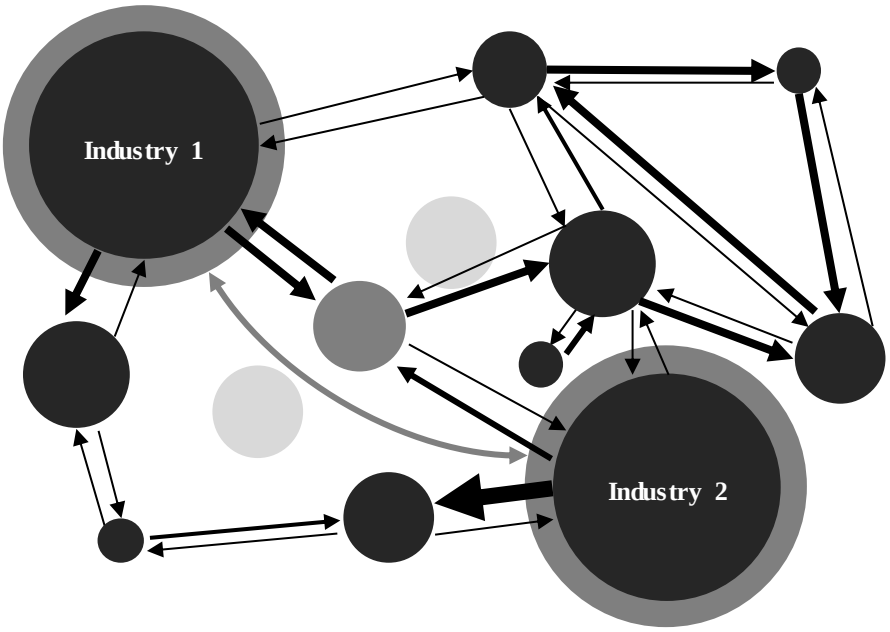


Figure 5: Representation of cross-specialization as closing a structural hole. Node size represents economic/scientific importance of an industry; tie thickness stands for degree of relatedness between industries.

The theoretical arguments underlying our notion of cross-specialization imply that promising innovation opportunities reside in industries that are connecting unrelated but highly competitive knowledge domains. Firms nested in such 'structural holes' in the industry space can be expected to have a relatively high potential of identifying breakthrough innovations. This leads us to stress that policy makers should be concentrating their support on (overcoming the coordination problems that hamper) the emergence of cross-specialized niches, rather than on the existing specializations themselves. A problem here, however, is that it is hard to know beforehand which niches will emerge out of the interaction between specialized industries. What policy makers can do, one could argue, is to investigate which industries have a knowledge brokering position in the existing industry structure. As firms in these cross-over industries are well-positioned for translating knowledge from one specialization to another, they might be important to involve in efforts aimed at creating cross-specialization interfaces (e.g. a joint innovation agenda, a shared research or production facility, a campus, a service innovation lab, etcetera).

The previous sections were focused on arguing why policy makers can benefit from a (possibly service-based) cross-specialization strategy. Building on the observation that some industries are well-positioned to be involved in bridging strong but unrelated knowledge domains, we now discuss the issue of identifying such industries. Following from the logic described above (see also Figure 5), which industries have a cross-over position can be determined by calculating cross-over centrality measure *X*:

$$X_i = \sum_{j}^{n} S_j * R_{i,j}$$

- X_i is cross-specialization-index for industry i.
- S_j is 'size' (economic/scientific importance) of surrounding industry j (j ranges from 1 to n).
- $r_{i,j}$ is relatedness in product space (between industry i and j).

The presented formula is based on the idea that specializations are covered by individual industries. In practice, most countries having industry policy focus on stronghold 'sectors' (or clusters) consisting of a number of closely connected industries. This implies that the most interesting cross-overs are not simply the ones linking unrelated but strong industries, but rather those who link unrelated but strong industries *from different stronghold sectors (clusters).* In the following sections we will illustrate empirically how centrality calculations can be applied to identify cross-over industries in the context of an economy containing stronghold sector

4.2 Cross-over industries in the Dutch Topsector industry space

The Netherlands are amongst those countries adhering to industry policy. Although the innovation policy mix also contains a large generic part (mainly tax incentives), the past few multi-annual R&D&I-programmes were marked by a specific focus. As of 2011, the government is supporting innovation in a total of 9 excellence domains. These so-called Topsectors were selected through a bottom-up process in which public and private actors could present themselves as candidates. Together, the Topsectors account for about 25% of Dutch firms, 36% of Dutch production value, 25% of added value, 20% of employment, 40% of exports, and 87% of R&D investments (2012 figures).[3] Recently, the linkages between the Topsectors have been gaining policy interest.

Identification of cross-over industries requires a measure for the relatedness between industries. Highly suitable in this respect is the concept of skill-relatedness, which refers to similarities between the skills and knowledge required for economic activity in different domains. While it is

[3] Netherlands Agency for Statistics (CBS) – *Top sector monitoring study 2014*. In Dutch.

common to state that firms in different parts of a value chain share similar knowledge, a skill-based perspective underlines that activities in for example the first part of one value chain are more similar to activities in the first part of another value chain (rather than to activities later in the own value chain). A database for inter-industry skill-relatedness was constructed by Neffke et al. (2011), who analyzed Swedish labour mobility over the period 1969-2002. A follow-up study in Germany has pointed at the robustness of the findings by Neffke et al. (2011), which makes their database suitable for application in a similar economy like the Dutch one (Neffke et al., 2012).

Using Neffke's skill-relatedness data, the network depicted in Graph 1 represents a part of the industry space of the Netherlands.[4] The nodes (and their colors) refer to which Topsector a certain industry belongs; non-Topsector industries are not shown here. [5]

Due to the bottom-up nature of the selection process, the designated Topsectors are not easily captured by NACE-codes. However, several recent efforts have resulted in lists of which NACE-categories make up a certain Topsector.[6] While there is a slight amount of overlap, most of the Topsectors cover a distinct part of the industry structure.[7] For reasons of clarity, also edges with a skill-relatedness value below 15 and statistical significance above 0.05 have been excluded (see Neffke et al., 2011, for details on calculation of these values). The size of the nodes reflects employment in the remaining industries (2009 figures, CBS). Node position, finally, is determined by a multidimensional scaling algorithm which tries to minimize tie lengths. A result of this technique is that nodes with many ties tend to gravitate to the center of the network graph; we will highlight this when discussing the issue of cross-over centrality.

INSERT GRAPH 1 HERE

Looking at the network graph of the Dutch Topsectors, it immediately becomes clear that most of the chosen strongholds consist of a relatively coherent set of industries (in terms of skill-relatedness). The colored circles indicate which type of sector is most dominant in a certain part of the depicted industry space.

The green area in the right-hand side of the graph contains industries from both 'Agri&Food' as well as 'Horticulture & Propagation materials'. This mix is not surprising, as the overlap in Topsector-classifications concerns in particular this part of the economy: all shown horticulture-industries, except Wholesale of alcoholic beverages (NACE 5134), are also part of the agriculture-Topsector. We therefore will refer to the agriculture sectors as if they were one Topsector.

On the left-hand side of the graph we find a relatively homogenous set of industries (with respect to Topsector-type) belonging to 'High Tech Systems and Materials' (HTSM). This set borders to a 'clique' of Water-industries (upper part of the graph) and industries from the Topsector 'Life Sciences and Health' (LSH). According to the skill-relatedness measures by Neffke et al., (2011), professionals in HTSM share relatively a lot of knowledge and capabilities with both Water and LSH, but Water and LSH are not at all related to each other.

Right in between the HTSM and Agriculture sectors, industries from the 'Logistic' Topsector are situated along the vertical axis within the industry space. This reflects the notion that logistic service providers are of relevance to a wide variety of economic activities. Rather than that professionals specialized in transport or storage flow mostly to one particular Topsector, we find that

[4] For the sake of clarity and brevity, we exemplify cross-over identification by only using the *outward* flows in the data.
[5] Symbols for the Topsectors taken from: Dutch Ministry of Economic Affairs (2013), *Progress report Enterprise Policy*.
[6] We draw upon the classification presented in the report by EIM (2012): *Snelle groeiers in de topsectoren*. In Dutch. The industry classification based on NACE Rev 1.1 matches with the NACE-version used by Neffke et al. (2011). The numbers in Graph 1 and onwards refer to the industries lasted in NACE Rev 1.1, where also the full industry name can be found.
[7] In the graphs each industry has only one color, but in our calculations based on sector types we took into account that some industries have multiple sector types.

the interconnections of Logistic industries are relatively diversified. For instance, Cargo-handling and to a lesser extent Sea and coastal water transport and Other water transport are found nearby the Water-clique; Storage and processing appears to share skills with the processing and sales of food (i.e. Agriculture-clique); and Logistic-related industries like Activities auxiliary to financial intermediation or to insurance and pension funding (respectively NACE 6713 and 6720) are similar to the activities common in the Creative industries.[8]

Together with the Logistics-industry Management activities of holdings (7415), we also find industries belonging to 'Chemicals' in the very core of the Topsector industry space. The relatedness-links of these industries are distributed over a relatively high number of Topsectors as well. This is what causes the Chemical-sector to end up as a circle in the middle of the graph: some chemical industries relate mainly to agriculture, others to HTSM, and yet others to LSH.

Industries classified as 'Creative industry' appear at the lower part of the graph, almost outside the main network. Although one might conclude that creative industries are not related to any other sector at all, the contrary might be true as well. Exactly because skills and knowledge are relevant for virtually every industry, there is no clear pattern of relations leading creative industries to be located near some particular other sector. Compare this with the Logistics and Chemicals sector, both of them consisting of industries mainly having *specific* cross-overs with other parts of the network. As knowledge from creative industries might be of common relevance, the only significant linkages emerging in the data of Neffke et al. (2011) are the ones within the creative domain.

Finally, only two industries from the 'Energy'-Topsector (yellow) have sufficiently high skill-relatedness values to appear in our network graph (SR>15). While Extraction and agglomeration of peat appears to be related to the Agriculture and Water-sectors, Manufacture of refined petroleum products is right in the middle of the graph. Indeed, this sector is adjacent to HTSM, Chemicals, Logistics, and the primary sector activities found in some Agriculture activities.

Not all industries shown in Graph 1 seem to be part of a Topsector-specific clique. Remarkable exceptions are Manufacture of tractors and of 'other agricultural and forestry machinery' (NACE 2931 and 2932). Both industries are far more skill-related to the HTSM-industries than to the other agriculture industries. Similarly, firms in the industry Manufacture of industrial gasses draw on skill-base more related to Agriculture than to other industries of the Topsector Chemicals.

Now that we have introduced the composition of the Dutch Topsectors, we can assess which industries can be regarded as strategic cross-overs. Our first observations already provide some indications of which industries are boundary spanners. The basic formula discussed above allows for several more variations in the determination of cross-over centrality. We will discuss a number of alternatives while referring to the graphs depicted in the end of this Appendix.

Cross-over centrality type 1: The product of industry importance and relatedness

Our initially suggested way to calculate an industry's cross-over centrality is by summing the product of the economic importance of the industries it is related to (size 'S') with the strength of the skill-relatedness with these industries ('R'). Essentially this is just a size-weighted version of a regular centrality measure (based on summation of the number or strengths of ties), as captured in the formula introduced earlier on:

$$X_i = \sum_j^n (S_{j1} * R_{j1})$$

[8] One could question whether these types of industries are rightly classified as Logistics, but this is no concern for the illustrative purposes of this section.

In Graph 2, and in all subsequent network graphs, the calculated centrality values are visualized as an industry's node size. Also, the relative position of the nodes remains equal to the initial configuration in Graph 1.

What Graph 2 shows is that the centrally located nodes are typically those deeply embedded in a particular Topsector. The remarkable centrality of the industry Manufacture of metal structures (NACE 2812) exemplifies this rather well. With the exception of some other HTSM-industries, many of the central nodes are located at the edge of the industry space. Likewise, while nodes from for instance the Chemical-sector are connected to a high number of other sectors, there is no central Chemicals-industry to be found in Graph 2. The provided results also show that being strongly related to one or a few big industries can already be enough for emerging as central. This is for instance the case for industry 6340, receiving it's centrality from its link with large industry 6010. Note that node 6010 is not central, since the network is directed rather than symmetrical (because we only take into account outward skill-flows, as mentioned in footnote 4). Something similar seems to hold for agriculture-node Manufacture of grain mill products (1561). In the upper right corner of the agriculture Topsector, we find four industries boosting each other's centrality due to their strong interconnectedness; all of them concern either farming or growing crops/cereals.

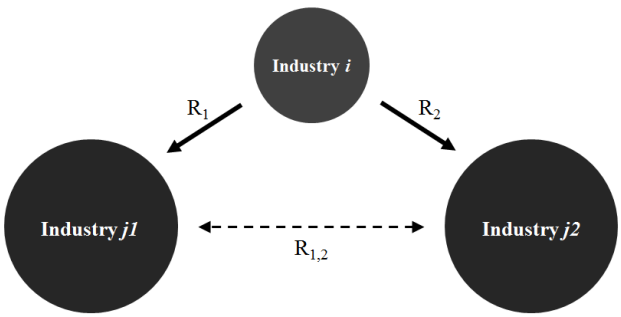
Our findings are consistent with the earlier observations that industries tend to be particularly skill-related to industries of their own Topsector. By defining cross-overs simply as industries having strong links with other (big) industries, we appear to arrive at a measure representing which industry is most central *within* a Topsector. In other words, many of the large nodes in Graph 2 are only a cross-over between various parts of a single Topsector. Reasoning from cross-specialization logic, our interest lies more at centrality-measures determined by a wider part of the industry space than only the densely interconnected set of immediately adjacent neighbors. This is what we will turn to now.

INSERT GRAPH 2 HERE

Cross-over centrality type 2: Connecting unrelated industries

In order to avoid that cross-over centrality is determined by the degree an industry is embedded in a clique of industries sharing similar knowledge, we adapt our centrality measure by imposing a restriction to the node-tie combinations that are being summed. Whenever an industry is strongly linked to two industries that are linked to each other as well, these edges are dropped from the summation. The altered formula, showed and illustrated below, requires us to aggregate (for each industry i) the node-tie products of all combinations of non-closed triangles. This way of measuring centrality fits better with the notion of knowledge brokerage; industry *i* closes the structural hole between industry *j1* and *j2*.

$$X_i = \sum_j^n \left((S_{j1} * R_{j1}) + (S_{j2} * R_{j2}) \right), \text{ in which } Rj_{1,2} = 0.$$



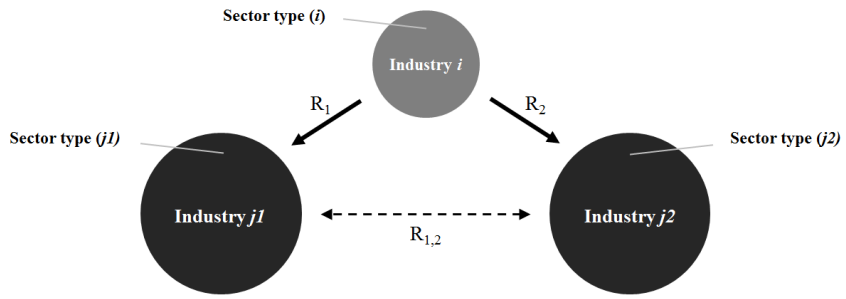
Graph 3 reveals how the adapted centrality measure results in several shifts in the centrality hierarchy. HTSM-industry 2812 is still relatively central, although overtaken by Manufacture of grain mill products. This latter industry forms the hub between a number of food-industries hardly connected to each other (e.g. manufacture of rusks and biscuits; of ice cream, of fresh pastry goods; of mineral waters and soft drinks). Because the farming and growing industries in the upper right corner are so connected in each other, several of them now have a much lower centrality than before. Another remarkable change is the sudden cross-over centrality of two industries at the core of the graph. Both Management activities of holdings (7415) and Manufacture of perfumes (2452) are now part of most central nodes. As they have links to a wide variety of sectors, and most industries are especially linked to industries within their own sector, these sectors close relatively many triangles in the Dutch Topsector industry space. This result appears also because, although situated very nearby, both industries are not linked to each other.

INSERT GRAPH 3 HERE

Cross-over centrality type 3: Connecting unrelated industries of a sector type other than ego

The last centrality measure gave us a better impression of which industry truly lies at the interface of many unconnected but large industries. Yet, by introducing an extra constraint we can still enhance the cross-over identification procedure. The fact that policy support is often directed towards a knowledge domain (Topsector) covering multiple rather than one industry implies that cross-specialization opportunities occur especially in economic activity at the boundaries of these domains. We therefore modify our previous calculation by imposing the requirement that node-tie products are only added to an industry's centrality value when the related industry is of another (Top)sector type. The condition that only brokerage positions count is maintained here, which we express as follows:

$X_i = \sum_j^n \left((S_{j1} * R_{j1}) + (S_{j2} * R_{j2})\right)$, in which $Rj_{1,2} = 0$. Type(i) ≠ Type (j), but Type (j1) can be Type (j2).



The pattern emerging from applying this third centrality calculation is highly different from the previous ones. Management activities of holdings (7415) and Manufacture of perfumes (2452) turn out to be the most central industries when it comes to being positioned as a cross-over between unrelated industries from different Topsectors. The fact that we do not count linkages with industries of their own Topsectors is hardly of any influence: industries from both Logistics and Chemicals were already found to be relatively dispersed rather than forming a dense Topsector-specific clique.

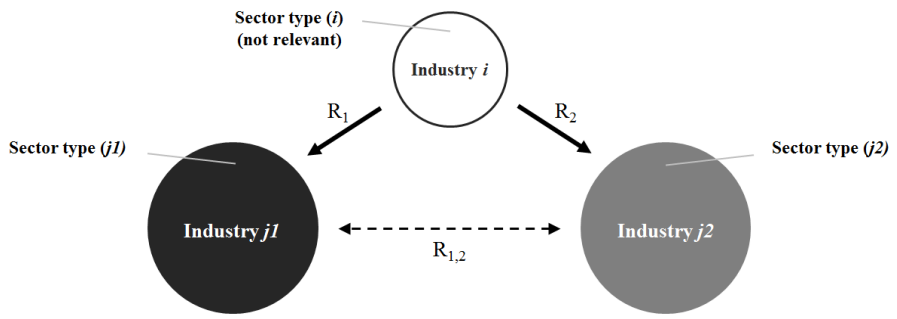
Graph 4 also points at the cross-over centrality of the HTSM-industry Manufacture of industrial process equipment (3330). This result is explained by its strong connections with several tool manufacturing industries (2942, 2943, 3110) combined with a link to the fruit growing industry (113). As the latter industry happens to employ many people in the Netherlands, but is not connected to any of the tool making industries, it has a high impact on the centrality value of industry 3330.

INSERT GRAPH 4 HERE

Cross-over centrality type 4: Connecting unrelated industries having different sector types

The constraint introduced in the last centrality calculation can also be applied for identifying cross-over industries in an alternative way. Instead of focusing on relatedness-ties with industries having a different type than a focal industry's own, we now ask which industries lay in between industries that are unrelated and heterogeneous in terms of their sector type. Such a measure of 'betweenness centrality' approaches the notion of brokerage in a manner that slightly differs from the previous centrality measure. Whereas the third type of calculating cross-over centrality highlights industries related to especially non-ego Topsectors, this fourth and last type should reveal which industries form the link between large industries from different Topsectors. As the formula and illustration below indicate, a focal industry's own sector-type are of no concern here.

$X_i = \sum_j^n \left((S_{j1} * R_{j1}) + (S_{j2} * R_{j2})\right)$, in which $Rj_{1,2} = 0$. Type(j1) $\neq$ Type (j2). Type(i) is irrelevant.



The last network graph, depicted in Graph 5, appears to be almost identical to the one resulting from cross-over centrality type 2. The constraint that centrality is determined only by bridging industries stemming from different Topsectors proves to be of little influence, given that such linkages are scarce anyway (compared to within-Topsector linkages).

Although the fourth type cross-over centrality seems to be redundant with the second one, there still is a merit to focusing at linkages between different sector types. So far, we only have been looking at industries falling under one or more Topsectors. An interesting possibility for creating cross-overs emerges when we also take non-Topsector industries into account. Examining which of such industries are skill-related to important industries from different Topsectors opens a new perspective on which kind of knowledge to use for making strongholds more alike. Arguably, the skills and knowledge present in cross-over industries not belonging to any Topsector are of relevance for reducing cognitive distance exactly there where fruitful synergies between Topsectors so far fail to arise. As such non-Topsector industries might be overlooked by the joint activities (e.g. strategic R&D programs) set up by any of the individual Topsectors, it is possible that this neglect prevents the emergence of knowledge flows with a high potential for generating breakthroughs innovations or promising niches (see argumentation provided in main text).

INSERT GRAPH 5 HERE

Graph 6 depicts the entire Dutch industry landscape, with node size still representing cross-over centrality type 4.[9] Non-Topsector industries are colored in blue. It is remarkable how many of the most central non-Topsector industries are situated somewhere between Agriculture, Logistics, Chemicals, and the Creative Industries. A look at what type of activity is to be found in these cross-overs reveals that all of them are in fact trade industries, the most important one being: wholesale of coffee, tea and spices (NACE 5137), wholesale of meat and meat products (NACE 5132), retail sale of cosmetic and toilet articles (NACE 5233), and other retail sale of food, beverages and tobacco (NACE 5227).

As an exception to these findings, the non-Topsector industry ultimately best-positioned to fill a structural hole between large Topsector industries is Motion picture and video distribution (NACE 9212). Still basing our calculations on employment figures and the skill-relatedness measures by Neffke et al. (2011), we observe that the skills found in this industry are related to unconnected industries from three different Topsectors (and a number of other non-Topsector industries). This is shown in Graph 6. While the similarity to other motion picture and publication activities is evident, the linkages with agriculture industries are perhaps more surprising. A reassuring result also shown in Graph 6 and 7, however, is that also Data base activities (NACE 7240) turn out to be a strong cross-(Top)sectoral link. This last finding is in line with our claims that services based on the collection and analysis of data are an example of activities with a high relevance for a high variety of industries. In the core of this chapter we described various possibilities for using this insight to create interfaces between unrelated sectors. Looking at the Dutch Topsector policy, we find that various instruments have been deployed to encourage especially SMEs in using facilities where they can experiment with novel ICT-technologies (for instance related to big data analysis or the Internet of Things).[10] The purpose of these initiatives is not just to help individual SMEs; by setting those firms together, the government is also allowing them to interact with and learn from each other.

INSERT GRAPH 6 HERE
INSERT GRAPH 7 HERE

5. Conclusions

This paper's main contributions are related to the goal of finding an alternative way for policy makers to capitalize on traditional stronghold industries. A major caveat in this respect is the danger of confusing the status of specialized knowledge bases: instead of being a basis for future competiveness they sometimes only are the result of past excellence in certain domains. In order to sustain the success of path-dependent configurations of knowledge, experience and institutions, policy makers need to identify ways for making stronghold industries adaptive to changing market circumstances.

The proposition we make is that special opportunities reside in linking strong but unrelated knowledge bases. Since multiple domains can contain deep knowledge, recombining these used components unites the advantages of being well-positioned to identify anomalies and being highly familiar with components on the one hand, with the breakthrough potential of recombining unrelated knowledge on the other hand. The challenge for policy makers is to overcome unrelatedness by making knowledge bases converge. So far, such a dynamic perspective on industry evolution has hardly been touched upon in the literature (Castaldi et al., 2014; Neffke et al., 2011). This paper thereby provides specific pathways for research and policy strategies pertaining to the dynamics underlying regional diversification.

[9] The construction of this measure is based on (Top)sector type. Non-Topsector industries do not have a Topsector-type, so being related to one of them does not contribute to an industry's centrality. However, of course it is possible to calculate the centrality of the non-Topsector industries themselves (while still only counting links with Topsector industries).
[10] See: http://www.doorbraakmetmkb.nl/ (In Dutch).

Compared to a backing winners approach, in which policy makers select a number of industries which will receive policy attention, focus on the intersection of strongholds might lead to a greater amount of variation in a region's overall knowledge base. While 'classical' industrial policy risks overlap with respect to the industries that are being regarded as unique, this problem holds less for the linkages between them (given that the number of possible linkages exceeds the number of industries). Moreover, Jacob's externalities suggest that exploration of novel knowledge combinations makes an economy more robust (future-proof) than exploiting the knowledge that proved to be successful in market conditions that might not last forever. In sum, cross-specialization tries to combine advantages of unique hard-to-imitate knowledge bases with the evolutionary imperative of increasing variation. Thereby, our propositions fit in ongoing efforts of using evolutionary economics as a basis for policy formulation (Schubert, 2014).[11]

5.1 Policy implications

We introduced three forms of cross-specialization, all of them having the potential to spur the kind of knowledge flows that can drive economic differentiation. Policy options associated with the various types of cross-specialization should be based on exploitation of the existence of different specialist knowledge bases by supporting uncommon but relatively promising forms of knowledge recombination. Here, one can think of designing training programs where firms from unrelated (and thus generally non-competing) strongholds can jointly experiment with knowledge with relevance for all of them. An example briefly mentioned is knowledge on service-based business models and service delivery, which fulfils the requirement of being useful for, yet poorly understood by, a broad range of firms. Apart from identifying which knowledge urges are shared by unrelated strongholds, policy makers can also facilitate their interaction by offering research facilities open to joint experimentation.

As for our empirical analyses, the various ways to examine cross-over centrality demonstrate which industry-intersections are particularly interesting when using cross-specialization logic. Industries observed to central in the Dutch Topsector landscape are, amongst others, one from Logistics (Management of holding companies) and one from Chemicals (Manufacture of perfumes). A closer inspection of the industry space reveals that it is not always sensible to focus on entire Topsectors; both the Logistics and Chemicals sector appear to be centrally located because they consist of industries highly related to industries from other Topsectors. For the Creative Topsector it seems that its industries are related to so many other parts of the economy that clear cross-over patterns can no longer be discerned. We also pointed at the importance of taking non-stronghold industries into account when searching for bridges between strongholds.

We once more emphasize that we do not necessarily plea only for 'vertical industry policy' focused on the cross-over industries: the purpose of this paper is to demonstrate how we can get a better view of the skills and knowledge that can be relevant for overcoming unrelatedness between strongholds. While sometimes it might be promising to support knowledge production and application in a centrally located industry, other times it is merely the type of knowledge possessed in this industry that is of importance. An example here is the observed cross-over centrality of 'Database activities'; policy makers can choose to support firms from this sector in their innovation activities (risking that only these firms will appropriate the rents), or policy makers choose to support of the spread of data collection and analysis skills.

[11] We do acknowledge that a policy approach directed at exploiting the knowledge of particular industries seems to be at odds with the laissez-faire approach that is usually suggested by evolutionists. Note however, that we build on the evolutionary-inspired principles of considering related variety when searching for ways to exploit a region's path-dependent configuration of knowledge and institutions (cf. Frenken et al., 2007). In fact, we extend this view by arguing how also unrelated knowledge bases can be used for creating novelty (Fleming, 2001; Castaldi et al., 2014). A focus on overcoming cognitive distance between disparate knowledge bases is substantially more evolutionary than the classical way of industry-policy.

There is a host of opportunities to make actors from unrelated strongholds interact with each other. One possibility, based on cross-specialization type C, is to establish collaboration around certain horizontal themes (notably societal challenges and multipurpose technologies). These horizontal themes might best be employed when fitted to the context of the specific strongholds that are being linked to each other. The actual design of stronghold-interfaces is therefore likely to benefit from more focused investigations into the particular needs and trends relevant for the specific strongholds involved. While developments like the rise of 3D-printing technologies can affect business practices in any part of the economy, opportunities and needs shared by a select set of industries can perhaps best be unleashed by setting up a targeted rather than universal approach. This is to say, when boosting 3D-printing activities in for instance life sciences and chemicals, this asks for a different approach than policy efforts focused of the adoption of 3D-printing in general.

5.2 Directions for future research

One of the most needed types of research following up on this study should be the identification of actual policy designs fitting with the cross-specialization strategy and its specific manifestation forms. Such inquires can be structured around the lines of knowledge types (i.e. which kind of knowledge has potential for use in mutual learning programs?) and knowledge platforms (how to bring parties together?).

In order to strengthen evidence for the cross-specialization approach, also the confirmation of our hypothesized mechanisms would be a fruitful addition. We stress that the reported cross-over identification procedures are only some first explorations. Future research can benefit from the use of more recent data, especially of a type representing better which industries truly matter for an economy. Instead of dealing with employment figures, like we did, one could think here of data on added value, exports, profits, investments, etcetera. Moreover, as the NACE classification is an international standard, it is recommended not just to look at absolute figures. Benchmarking the performance of industries against industries from other countries would also contribute to a better indication of which industries to regard as strongholds. The relative performance of an industry can be expressed via location quotients, which would then replace the Size-parameter in our formulae.

Finally, we invite scholars to examine under which conditions cross-over industries indeed show (themselves) or cause (in other industries) upsurges in economic performance. Particularly interesting is the question how policy intervention following cross-specialization logic plays a role in such dynamics. With this paper we hope to provide measures for analyzing structural change based on knowledge brokerage.

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Appendix: The relation between related and unrelated variety

Related and unrelated variety are often thought of as opposites. However, by referring to different levels of hierarchy, the two types of variety essentially are "orthogonal in their meaning" (Castaldi et al., 2014). Indeed, multiple studies show they tend to be empirically correlated (Boschma and Frenken, 2011). These studies typically operationalize relatedness by looking at the concentration of economic activity according to hierarchical industry classifications like NACE and SIC.

Figure A.1 shows four extreme combinations of unrelated and related variety. In the lower left corner, one finds the situation where almost all economic activity is concentrated in main sector A. In this economic structure there hardly are any firms in the other unrelated sectors: main-level heterogeneity (i.e. unrelated variety) is very modest. Looking at lower levels of aggregation, the minor degree of distribution of economic activity over the subsectors (industries) means that the present firms are relatively similar to each other. The high share of firms in sector A is distributed over two subsectors, which we regard as being related, but apart from that most firms do not operate in an environment where there is a lot of economic activity in neighbouring subsectors. The degree of related variety is thus low as well. Related variety is higher when activity in one main sector is more distributed over the constituting subsectors. Similarly, unrelated variety increases when a substantial share of firms is active in other main sectors.

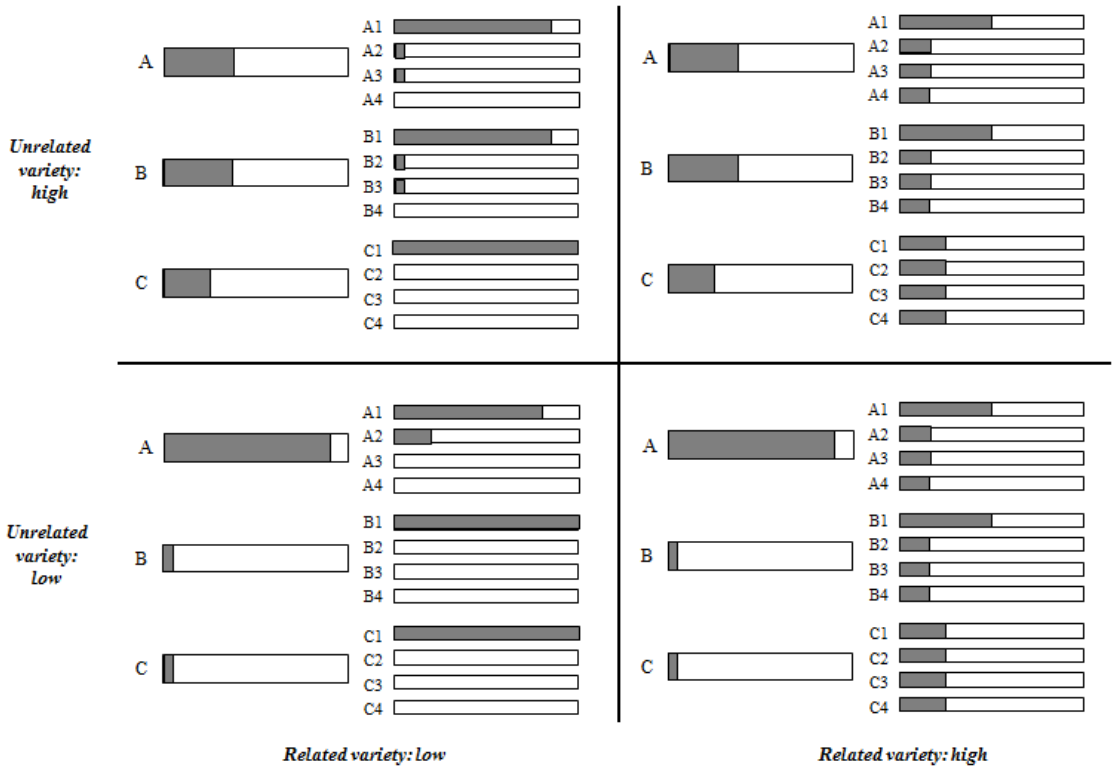


Figure A.1: Matrix with four combinations of related and unrelated variety. Bars represent how economic activity is distributed over three main sectors (together 100%), and over their respective subsectors (per sector together 100%).

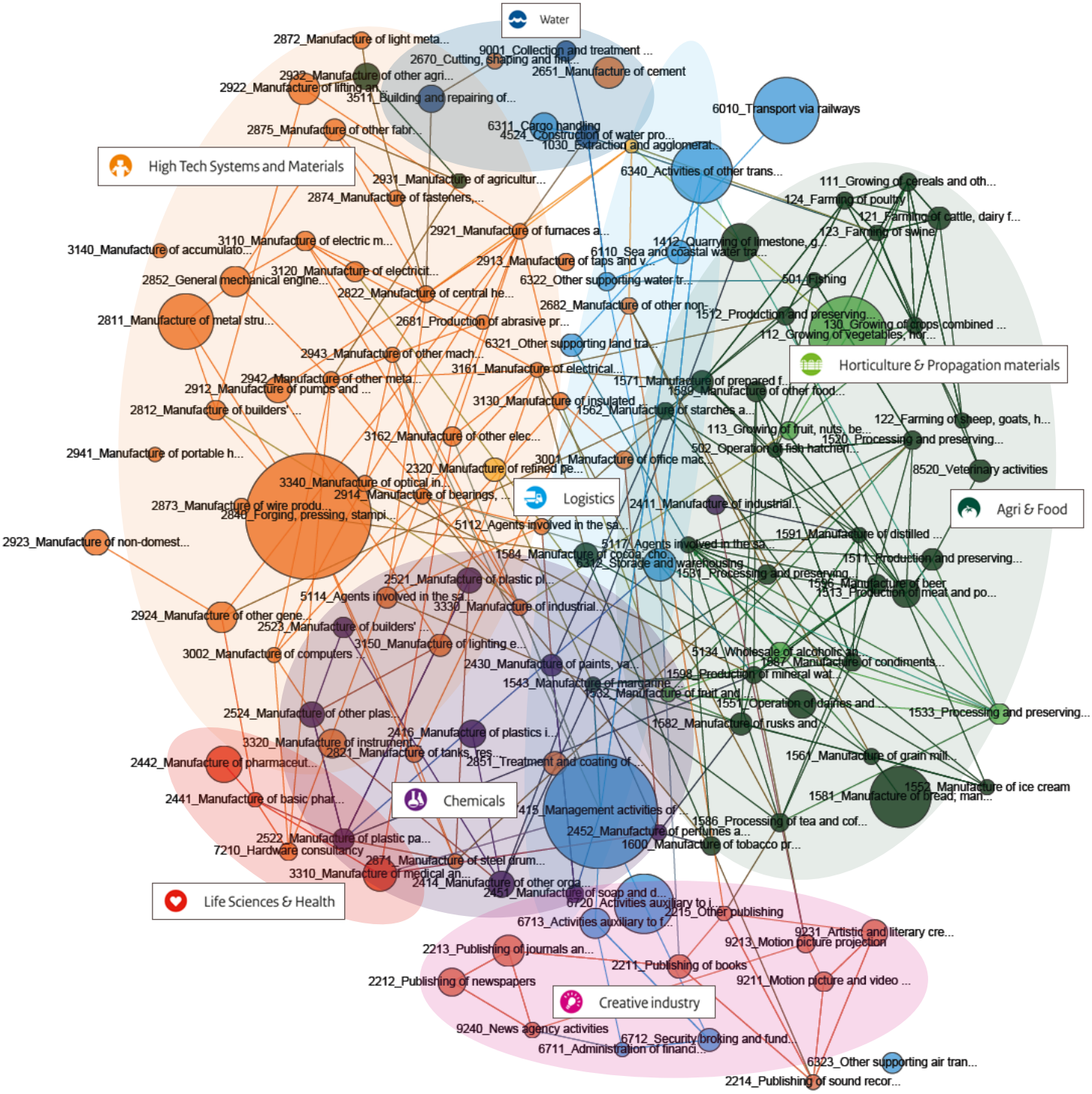
The fact that regions can be specialized in multiple unrelated domains holds important policy implications. A conventional approach, as noted, is to enhance the competitiveness and exploitation of such stronghold industries by nurturing further development of these distinct specializations. From an evolutionary perspective, the development of specializations would mostly benefit from having access to knowledge that can be used for innovative recombination.

Let us assume that a high concentration of economic activity in Figure A.1 marks a stronghold domain.[12] In the upper right quadrant, we have economic structures where such knowledge is available for actors in strongholds A1 and B1. Because there is a high level of related activity within their respective industries, those actors operate in the presence of parties with adjacent knowledge bases. The interactions that can naturally occur then form a basis for knowledge recombination within the stronghold industries.

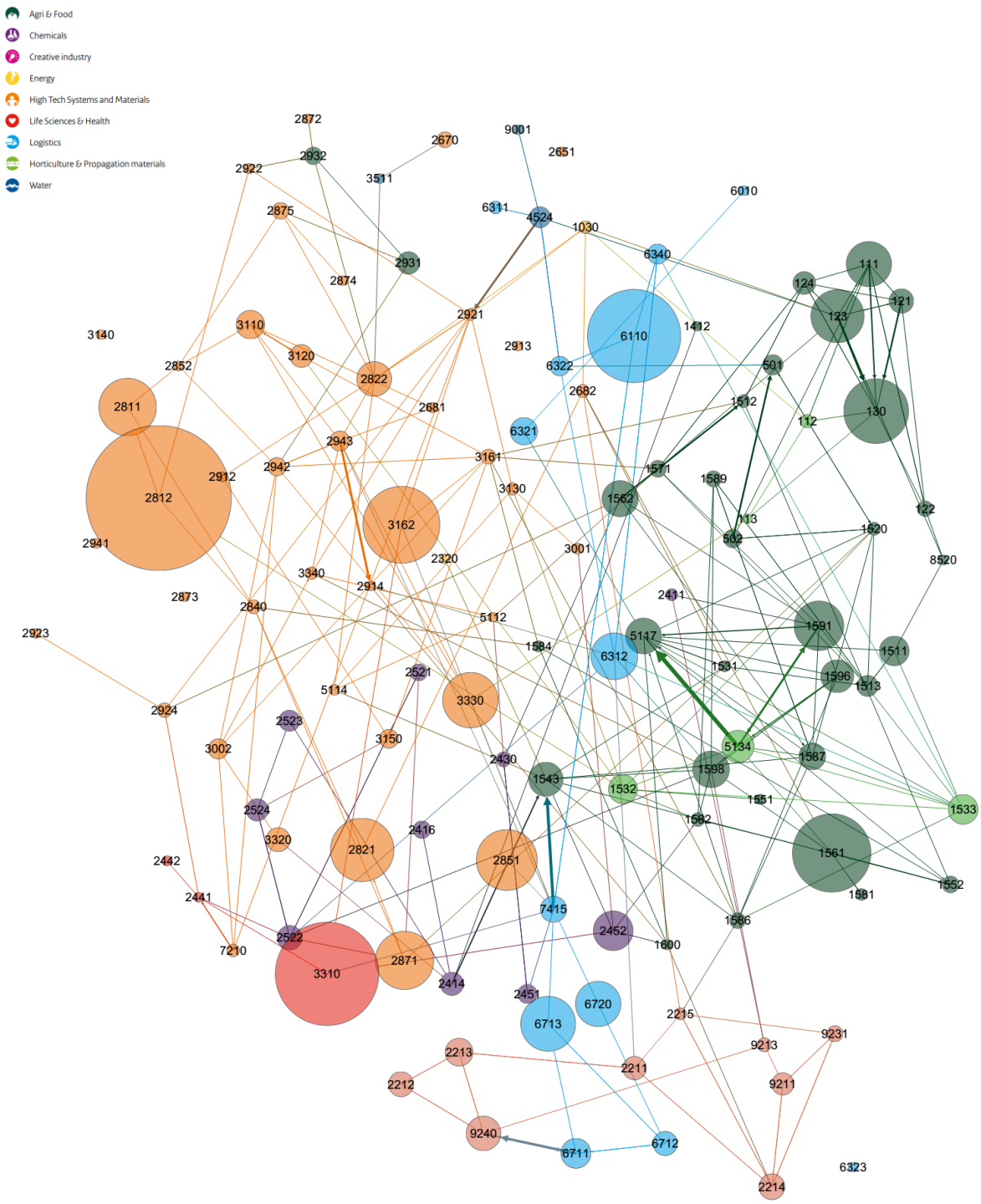
The situation is different for economic structures corresponding with the upper left quadrant of Figure A.1. Here we also find multiple strongholds (A1, B1 and C1), but the high degree of concentration within each of the main sectors leaves relatively little opportunities for generative knowledge exchange. The only knowledge that is locally available stems from industries with an entirely different knowledge base. If we ignore knowledge inflows from elsewhere, the present specializations can only be enriched with knowledge from another stronghold.

[12] Scientific, technological or even economic strength (e.g. export potential) in a certain domain do not necessarily imply that this domain also accounts for a large share of an economy's employment or output. Our simplifying assumption only serves to clarify how possibilities for knowledge exchange differ per quadrant.

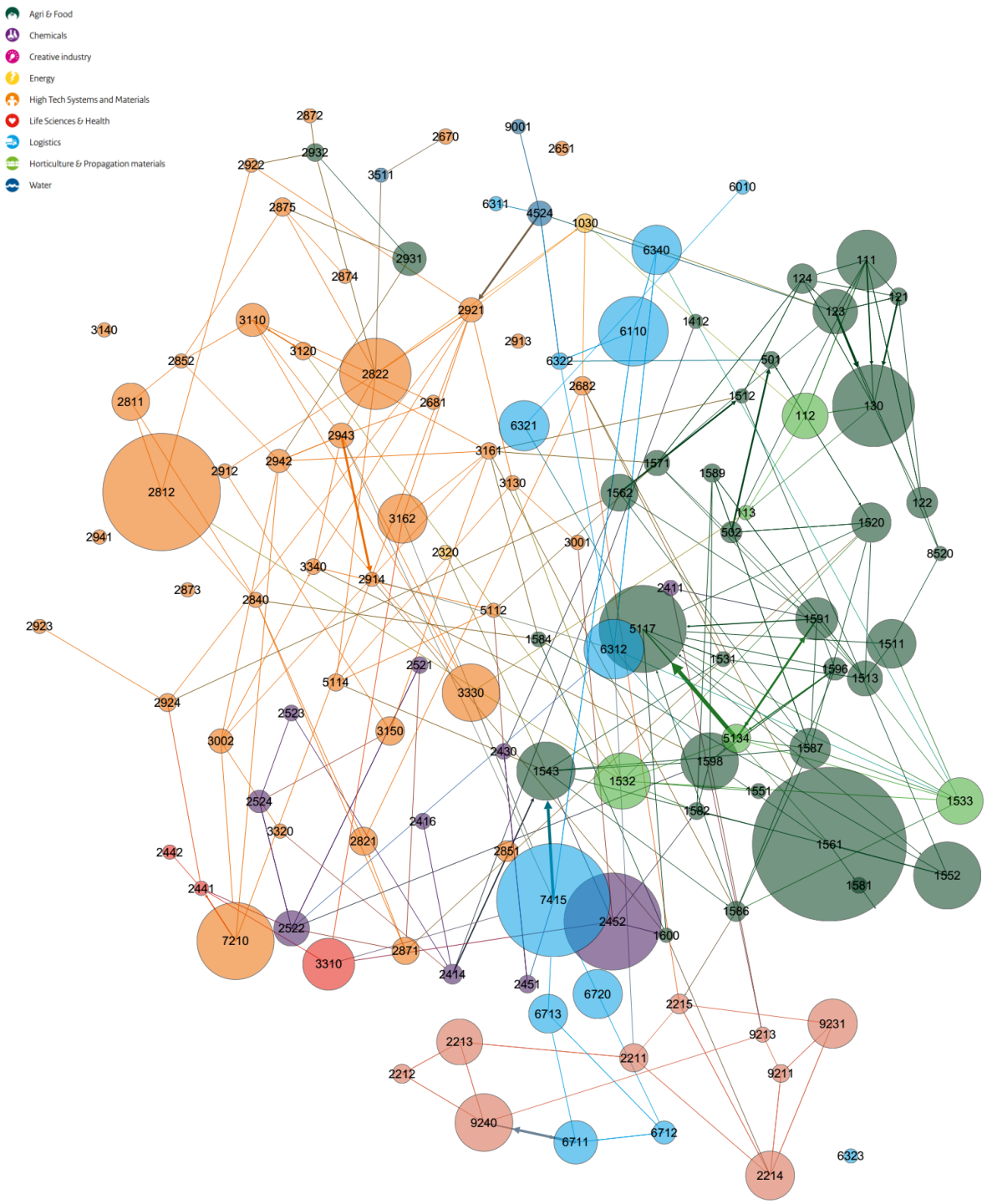
Graphs



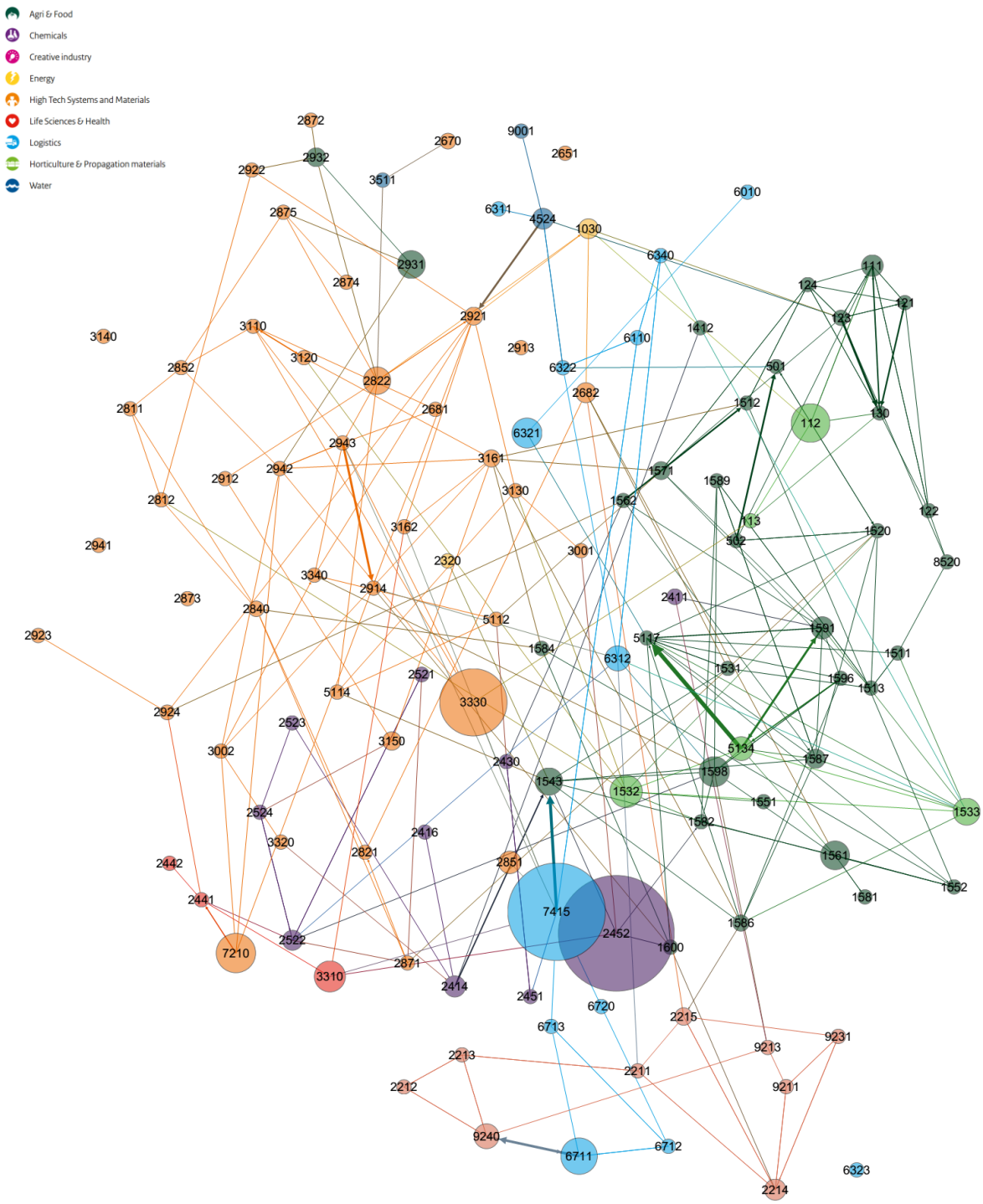
Graph 1: Topsector industries in the Dutch industry space. Node size represents employment (2009 figures); tie thickness stands for degree of skill-relatedness between industries (SR > 15, p < 0.05; see Neffke et al., 2011).



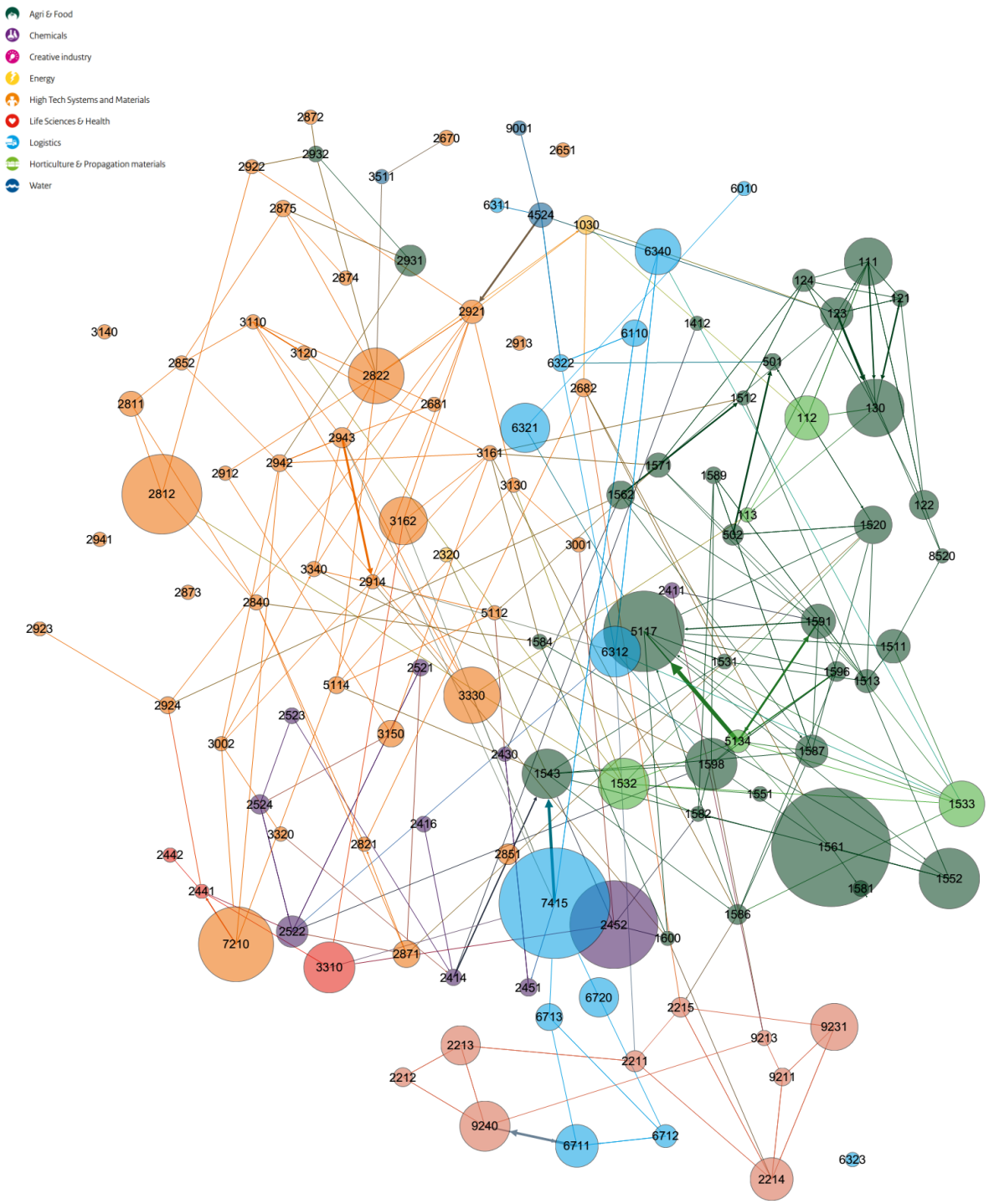
Graph 2: Topsector industries in the Dutch industry space. Node size represents cross-over centrality type 1 (the product of industry importance and skill-relatedness).



Graph 3: Topsector industries in the Dutch industry space. Node size represents cross-over centrality type 2 (the product of industry importance and skill-relatedness, but only for combinations of unrelated industries).

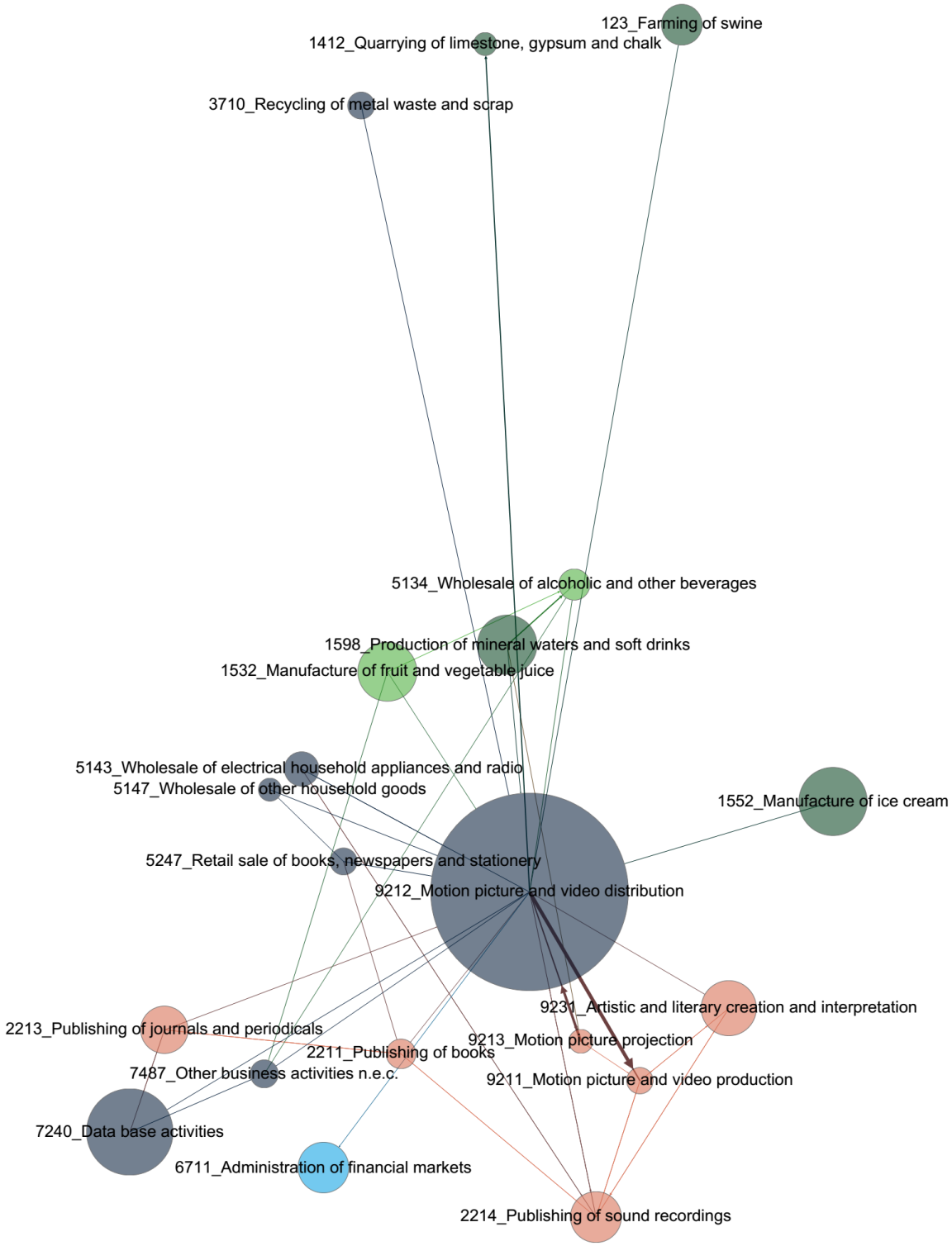


Graph 4: Topsector industries in the Dutch industry space. Node size represents cross-over centrality type 3 (the product of industry importance and skill-relatedness, but only for combinations of unrelated industries of a sector type other than the focal industry's own).



Graph 5: Topsector industries in the Dutch industry space. Node size represents cross-over centrality type 4 (the product of industry importance and skill-relatedness, but only for combinations of unrelated industries having different sector types). The box contains a network element consisting of highly central non-Topsector industries (dark blue).

Graph 6: The entire Dutch industry space. Node size represents cross-over centrality type 4. This also includes non-Topsector industries, in dark blue.



Graph 7: Section from Graph 6.