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Does the Position in the Inter-sectoral Knowledge Space affect the International Competitiveness of Industries?

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Abstract

This paper empirically investigates how the inter-sectoral knowledge flows affect the international competitiveness of industries, once controlling for both cost and other technological factors. Using patent data on 14 manufacturing industries in 16 OECD countries over the period 1995-2009, we apply a network-based approach to capture the effect of industries' position in the flows of technological knowledge across industries, which we label *inter-sectoral knowledge space*. We find that (i) centrality and local clustering in the inter-sectoral knowledge space positively affect the export market shares of an industry, (ii) such two effects are rather redundant and, (iii) national-level knowledge flows' impacts on international competitiveness are way stronger than international ones. Network measures of position in the knowledge space are found to be more relevant than standard technological indicators such as patent counts. Our results point to the importance of industries being well located in the stream of knowledge flows, rather than being innovative per-se, and offers an novel yet robust proxy to measure technological factors affecting trade performances. In addition, we find evidence of geographical boundaries of knowledge flows.

Keywords: international trade; industry competitiveness; knowledge flows; patent data.

JEL Classification: D85; F14; L60; O3

1 Introduction

The relationship between technology and the international competitiveness of industries - defined as the ability of a given country or industry to compete with its foreign counterparts (Castellacci, 2008) - has been central to academic research as well as economic policy. A large body of both theoretical and empirical literature has investigated the role of technology and technological change in influencing international competitiveness at micro, meso and macro levels (see, for example, Fagerberg, 1988, Amendola et al., 1993, and more recently, Laursen and Meliciani, 2010 and Dosi et al., 2015). Taking an industry-level perspective, the present paper proposes a complementary view to these contributions by isolating a novel and significant factor that explains the dynamics of competitiveness. We build on the notion of knowledge flows and rely on a network perspective to investigate whether the relative position of an industry within a relevant knowledge space affects the international competitiveness of that industry.

In the trade literature the investigation of technological factors in addition to cost-related ones dates back to the seminal work of Posner (1961), who posits that one of the main sources of (absolute) advantage of a country comes from its relative technological position against its competitors in any one activity. Since then and, particularly, since the second half of the 1980s, the literature has spurred. Following the evolutionary and disequilibrium perspective of Dosi et al., 1990, trade flows have been considered primarily driven by sector-specific absolute advantages, in turn stemming from widespread technological asymmetries between countries, due to differences in the capabilities to produce innovative products (i.e. which other countries are not yet capable of producing, irrespective of relative costs), to develop new process innovations or to use existing processes more efficiently or more rapidly. Along these lines, one may reasonably argue that the ultimate driver of sector specific advantages rests in the technical knowledge behind both product and process innovations (see also Dosi (1988) for a more general discussion). Indeed, following Fagerberg (1996), we can formally specify country-industry competitiveness as a function of both technological and cost factors.

Among technological factors, one may distinguish between innovative activity and the diffusion of advanced knowledge. Both factors have been widely examined in the literature. As far as innovation activity is considered, many have focused on the effects of knowledge production, patent stocks, R&D activities and national innovation systems on the competitiveness of industries and countries (Nelson and Winter, 1977; Freeman et al., 1982; Dosi, 1988; Dosi et al., 1990). With respect to the diffusion of advanced knowledge, while Grossman and Helpman (1991, 1995) have underlined the role of national and international knowledge spillovers, Laursen and Meliciani (2000, 2002) stressed the role of inter-sectoral linkages in affecting trade competitiveness. Our analysis builds on this last group of contributions. In particular, the purpose of the present paper is to empirically investigate how technology affects competitiveness not just directly, via the production of technical knowledge, but also indirectly, characterizing an industry's position in the network of inter-sectoral flows of knowledge - which we call the inter-sectoral knowledge space. The core idea, better detailed in the remaining of the paper, is that the position of industry might allow both the acquisition and the diffusion of relevant pieces of knowledge. In addition, we allow for a dynamic specification tracking how industries change their position in the network of knowledge flows. Our approach considers both national and international relationships among industries and makes use of patent data to identify and quantify links among them. In that, our representation of knowledge flows differs from the stream of research on the role played by the position in product space (Hidalgo et al., 2007; Tacchella et al., 2012), as we directly map technological relationships - using patent data - and their effects on the competitiveness of industries (rather than countries)[1]. We follow Breschi et al. (2003) in the construction of a "national" knowledge network in terms of co-occurrences of all pairs of technological classes included in the patent stock of each country. In addition, to study international flows, we focus on patent citations (Jaffe and Trajtenberg, 2002). Results show that (i) centrality and local clustering in the inter-sectoral knowledge space positively affect the export market shares of an industry of a country, (ii) such two effects are rather redundant, i.e. being central in a knowledge space is far less relevant when the industry is highly connected within a cluster and, finally, (iii) national-level knowledge flows affect international competitiveness much more than international ones do. Actually, the latter are even not significant in boosting export performances.

The paper is organized as follows. Section 2 presents a critical overview of the literature, while section 3 provides a discussion of mechanisms influencing international competitiveness and derives two main propositions. Sections 4 and 5 offer a description of the data and the

[1]Network methods have been employed to quantitatively measure the impact of relatendeness on diversification/specialization patterns of countries and regions. Recently, Alshamsi et al. (2018) and Petralia et al. (2017) provided evidence that the probability of diversification in terms of products, research areas and technologies increases with the number of related activities.

econometric strategy used in the paper. Then section 6 summarizes the results and section 7 concludes the paper.

2 The Relationship between Technology and Competitiveness

2.1 Technology, Costs and International Competitiveness

When examining international competitiveness, Schumpeterian insights have shifted the focus from cost-related variables towards technological factors. In this vein, following Dosi et al. (1990), a general formulation can be specified as a simple function of technological (T) and cost (C) variables:

$$Y_{ij} = f(T_{ij},\ C_{ij}),\ \text{with} \begin{cases} i & \text{stands for}\, Sector \\ j & \text{stands for}\, Country \end{cases} \tag{1}$$

where Y_{ij} is an indicator of international competitiveness such as export market share or trade balance.

The estimation of equation (1) generated a relevant stream of empirical literature pointing to the crucial role played by innovative activities and knowledge flows in explaining the international competitiveness of industries and countries. Due to data constraints, most of the empirical work within the "technological gap" framework has been carried out at country or industry-country level. In a pioneering empirical work, Soete (1981, 1987) provides some evidence of the relevance of technological factors as determinants of competitiveness. In a sample of OECD countries, across several sectors, results show a strong relationship between patent activities (as a proxy for technological performance) and export performance. At the country level, Fagerberg (1988) examines the effect of technological factors (patents, R&D) and of investments over unit labor cost (as a proxy for competitiveness) in order to explain growth in export market shares. Results are consistent with the so-called "Kaldor paradox" (Kaldor, 1978, was among the first authors to show that export market shares and relative unit costs or prices move towards the same direction.). Greenhalgh (1990) supports as well the idea that innovations sustain export performances and also finds (focusing on UK) stark heterogeneity across industries, with relative prices negatively affecting export only in few sectors. As far as the time dimension is concerned, Amendola et al.

(1993) report a positive and significant effect of technological variables (patents and investments) on export shares in the long-run. Unit labor cost plays a role only in the short-run.

Such results have been confirmed by analyses at level of country and industry. In particular, taking into account twenty countries and forty sectors, the cross-sectional analysis of Dosi et al. (1990) supports previous findings. Indeed, they clearly show that technological variables (investments and patent shares) positively affect several export measures, whereas cost-related factors (wages and unit labor cost) appear to have little or no effect.

Following a similar econometric approach, Magnier and Toujas-Bernate (1994) and Amable and Verspagen (1995) confirm the positive results for different innovation proxies (patents, investments and R&D). In addition, Wakelin (1998) uses bilateral trade flows and shows that R&D intensity and patents are crucial in high and low-technology sectors. Cost variables are instead significant only in medium and low knowledge-intensive sectors. Finally, Carlin et al. (2001) measure export market performance of OECD countries finding ambiguous results. Both costs and technology play a role in describing changes in export positions: however neither is sufficiently strong to fully explain such performances.

More recently, Guarascio and Pianta (2017) have analyzed the complexity of the so-called "virtuous circles" that link technological innovation, international competitiveness and profit dynamics. Building on previous work (Guarascio et al., 2015, 2016), they stress the relevance of *gains from technology* (vis-a-vis cost factors) in boosting trade competitiveness, confirming results in Dosi et al. (2015).

2.2 The Role of Spillovers and Inter-sectoral Knowledge Flows

In general, technology affects competitiveness not just directly, but also indirectly through technological spillovers. Griliches (1979) distinguishes two types of spillovers: "rent-spillovers" and "pure knowledge spillovers". Such distinction arises from several different mechanisms through which knowledge and technology can spread. In particular, spillovers embodied in products represent the specific category of rent-spillovers. Thus rent-spillovers cannot be assumed as pure externalities since they are intrinsically dependent on the market structure of supplying and using industries. Conversely, pure knowledge spillovers are mainly related to the technology and may constitute true externalities.

Along these lines, Grossman and Helpman (1991, 1995) theoretically investigate how international trade in commodities may boost the exchange of intangible knowledge and ideas as well as how differences between international and national spillovers contribute to the formation of the knowledge base.

In parallel to international trade analysis, evolutionary scholars have focused on the effect of innovation on the dynamics of firms and industries (Nelson and Winter, 1982; Dosi, 1988; Dosi et al., 1990; Freeman et al., 1982; Malerba et al., 2016) and on the role played by institutions and national innovation systems in affecting the growth and competitiveness of countries (Nelson, 1993; Freeman, 1987). The evolutionary and Schumpeterian literature has associated spillovers to technology and knowledge and shifted the focus from automatic pure spillovers to flows of knowledge that may run across firms and countries in less automatic way, often related to the role of absorptive capabilities of the recipient firm and country (Cohen and Levinthal, 1989, 1990; Cimoli et al., 2009; Dosi et al., 2008).

One key aspect of knowledge flows refers to inter-sectoral flows. This is related to the importance that has been given to industries and sectors in the examination of the international performance of countries. Inter-sectoral knowledge flows has been intensively studied with input-output data and technology flows matrices based on patents (Scherer, 1982; Putnam and Evenson, 1994; Verspagen, 1997a,b; Laursen and Drejer, 1999).

As far as input-output links are concerned, Scherer (1982) and Putnam and Evenson (1994) follow an approach based on the relationships between supplier and user industries[2]. As input-output links, a certain innovation/product generated by an industry $\mathcal{A}$ can then be used by an industry $\mathcal{B}$. Clearly, this way of reasoning is consistent with the notion of what we defined rent-spillovers (Griliches, 1979).

As far as technology flows matrices are concerned, Verspagen (1997a,b) proposes three different approaches to analyze pure technological spillovers. The first matrix they use relies on data from EPO and it is constructed on the basis of main and supplementary IPC codes. Such step is employed for claimable knowledge. The second matrix is derived following the same principle, although it takes into consideration the supplementary codes for unclaimable knowledge[3]. In practice the main code identifies knowledge producing-sectors, whereas spillovers

[2]The method is the backbone of the so-called "Yale-matrix" that relies on the Canadian Patent Office data.

[3]In the EPO data supplementary classes may contain invention information (claimable) and additional

are eventually captured through the relationships with supplementary IPC codes. Finally, the third matrix is constructed using citations in the US patent database. It is argued, of course, that knowledge flows from the cited to the citing patent sector. An alternative approach is proposed by Jaffe (1986), who measures technological distance among US firms on the basis of the distribution of firms' patenting activities[4]. It must be noted that most of the aforementioned works have been carried out with the purpose of quantifying the impact of spillovers on productivity and innovative activities[5].

In addition to the studies on spillovers, the "home market hypothesis" literature considers the effect of technological spillovers on international trade dynamics and specialization[6]. Particularly, it suggests that domestic inter-sectoral linkages are of paramount importance in explaining trade flows and specialization. The "home market hypothesis" has been empirically investigated by (Fagerberg, 1992, 1995)[7]. However, his empirical analysis only considers "backward linkages" and makes use of trade statistics and Revealed Comparative Advantage (RCA) to measure both competitiveness of the producers of technology and how advanced the domestic users are. Based on actual I-O data, Laursen and Drejer (1999) introduce upstream and downstream linkages as a possible technological source of export specialization. Such findings prove inter-sectoral linkages to be a determinant of specialization. However, the importance differs according to the type of sector (e.g. following the Pavitt taxonomy). Subsequenly, Laursen and Meliciani (2000, 2002) find a positive effect of national R&D linkages on competitiveness. Interestingly, they find that only national spillovers have a clear impact on trade balance. Differently, Laursen and Meliciani (2010) investigate the role of ICT knowledge flows and conclude that in ICT industries both national and international linkages have a positive effect on export market shares.

information (unclaimable).

[4]Formally, Jaffe (1986) employs the so-called *cosine index* to capture such distance.

[5]See Griliches (1998); Jaffe and Trajtenberg (2002) for a complete treatment of the topic.

[6]We will discuss the *home market effect* in greater detail later in the paper.

[7]Moreover, Fagerberg (1997) examined the effect of domestic and foreign R&D on export performance.

3 Industries' Position, Knowledge Space and International Competitiveness

3.1 Position

In this paper, we propose a novel way to look at inter-sectoral flows of knowledge. We shift the emphasis from the flows of knowledge related to bilateral industrial relationships to the position of an industry in the entire inter-sectoral knowledge space. The reason for such change is that the position of an industry in a technological space in terms of links with the other industries, both nationally and internationally, provides a more complete and articulated representation of all direct and indirect inter-sectoral knowledge flows that an industry has. For example, Antonelli et al. (2017) recently showed that the composition of local knowledge is a major determinant of innovative activities. Our approach also benefits from the literature concerning the measurement of technological relatedness and proximity in a broader sense. Indeed, the interaction among different dimensions of proximity results of paramount importance for learning and innovation (Breschi et al., 2003; Engelsman and van Raan, 1994; Boschma et al., 2014; Kogler et al., 2013). We advance the claim that an industry that is central in the flows of knowledge among sectors and that is highly connected with the other sectors, obtains major benefits in terms of competitiveness. We propose that the following three mechanisms may explain our claim.

Variety in Knowledge and Opportunities. A first mechanisms is that an industry that is central in the flows of knowledge across industries enlarges its opportunities to come across pieces of potentially useful knowledge and, hence, its chances to boost its market performances. This is consistent with the so-called "specialization-based" trade growth, which links trade performances to the ability to exploit above average technological opportunities arising in certain sectors (see Laursen, 1999, and references therein). In such a context, technological opportunities have been usually measured through growth rates in patenting activity (Cantwell and Andersen, 1996; Meliciani, 1998). However, Laursen (1999) shows that there is little empirical support for the hypothesis that being initially specialized in fast-growing industries yields a positive effect on trade performances. As extensively argued in Klevorick et al. (1995), technological opportunities in one industry can be enriched by technological advances that are achieved in others. Further, such an extra-industry source of technological opportunities positively and significantly correlates with both process and product innovation in the relevant industry. The relationship between opportunities and innovation has been investigated in various ways. Malerba and Orsenigo (1997) suggest that the the specific pattern of innovative activity of a sector can be explained by the structure of the underlying knowledge, which seize opportunities together with learning processes (see also Dosi, 1988). Empirically, Becker and Peters (2000) and Oltra and Flor (2003) confirm that technological opportunities from other industries sustain innovative performances in a sample of German and Spanish firms respectively. Cohen and Malerba (2001) point out that greater diversity in innovative activities results positively associated with faster technological change. Moreover, the existence of an inverted-U relationship between technological diversification and firms' technological performance (Leten et al., 2007; Garcia-Vega, 2006) suggests that the effect of broadening technological opportunities enhances performances, provided it does not become too high. Furthermore, the larger is the pool of opportunities and technological linkages, the lower are the chances that firms in a given industry remain locked in to inferior technologies. This effect comes from being exposed to a large learning basin and having the possibility to mold such flows into effective knowledge due to connections (Boschma, 2005; Balland et al., 2015).

Recombination. A second mechanism is that inventions and innovations develop more easily, and have a greater impact on the economic system (and therefore also on competitiveness), when firms combine knowledge across different technological domains, which in turn may belong to different sectors (Ferguson and Carnabuci, 2017; Fleming and Sorenson, 2001; Basalla, 1988). Scholars have found that a large part of technological advances comes to a good extent from multidisciplinary R&D (Kodama, 1986; Rosenberg et al., 1992). Moreover, both theoretical and empirical literature provide evidence that spanning knowledge domains might give inventors a wider vision of technological opportunities (Ferguson and Carnabuci, 2017; Hargadon and Sutton, 1997; Hargadon, 2002) while knowledge complexity substantially influences the diffusion dynamics (Sorenson et al., 2006). The idea that recombination might help creating something new and potentially useful goes back to (Schumpeter, 1934, pag. 65). Drawing on Galunic and Rodan (1998), we claim that recombination of resources - including knowledge - facilitate the creation of novel systems. Following these lines, being exposed to several different technological flows coming from different industries may reduce uncertainty and significantly increase the usefulness of innovation (Fleming, 2001). Hence, knowledge flows and technological linkages boost the possibility of recombining knowledge. Knowledge diffusion and the network structure of inter-sectoral relationships clearly affects the possibility to integrate different pieces of knowledge, especially for multidisciplinary innovation (Sorenson et al., 2006).

Improvement of Absorptive Capabilities. A third mechanism is that an industry exposed to knowledge coming from different other industries increases its absorptive capabilities of selecting, identifying and using various pieces of knowledge that can be relevant for its problem solving (Von Hippel, 1994; Owen-Smith and Powell, 2004) and innovative activities (Cohen and Levinthal, 1989, 1990; Lundvall and Johnson, 1994). In that, an increase in the absorptive capacities within an industry results from a successful process of learning and external knowledge management, which may be influenced by different - both geographically localised and not - factors (Boschma, 2005; Boschma and ter Wal, 2007; De Noni et al., 2017). Centrality in the knowledge flows increases the experience of firms in an industry in managing different types of knowledge. In addition, being exposed to knowledge coming from different industrial contexts increases the capability of understanding different application contexts (Christensen et al., 1998). If market success ultimately depends on the ability to channel R&D for attracting final demand rather spending in research activities per se (Iansiti, 1995), then being central in a network of knowledge flows from different industries increase the amount of information on fields in which a technology can be successfully exploited. Finally, Burt (2004) has witnessed how crucial network position (brokerage) and the development of organizational abilities are in influencing firms' innovative performance. To sum up, being exposed to knowledge flows may help industries develop technological as well as managerial capabilities to effectively master different technologies and eventually match them with the most appropriate context.[8]

We believe that a knowledge space approach offers new insights and fill the gap existing in the literature by merging together both social networks and absorptive capabilities lines of research. Recently, Duernecker and Vega-Redondo (2017) theoretically show that the social network is the main channel through which agents exploit new opportunities. In their empirical

[8] Along these lines, the interested reader may want to look also at the literature on the role of embeddedness in boosting performances at different levels (e.g. Ahuja, 2000; Andersen, 2013).

companion paper they found that centrality is a very significant variable in explaining differences in countries' growth performances (Duernecker et al., 2015). Operti and Carnabuci (2011) and Tortoriello (2015) provide additional empirical evidence consistent with the theoretical framework formulated here. A more structured modelization of knowledge space has been adopted by Tomasello et al. (2016) and Vaccario et al. (2017) in studying R&D alliances and knowledge exchange among firms. Finally, to these three factors related to knowledge, it is possible to add some remarks about the variety of channels and organizational forms through which knowledge crosses industry boundaries. While the channels that have been most widely studied refer to informal mechanisms (see for example Fagerberg et al. (2006)), personnel mobility between firms (for example Saxenian (1990); Almeida and Kogut (1999)), vertical integration (for example Helfat (2015)) and inter-organzational agreements (for example Hagedoorn (2002)), recently also channels related to new firms originated in the upstream or downstream industries that enter a focal industrial sector -i.e. vertical spinouts- have been studied (Adams et al., 2016, 2018). While this paper does not aim to examine the informal, individual or organizational channels through which knowledge flows across industries, it must be emphasized here that a channel may affect how much and what type of knowledge is transmitted. For example, in the case of new firms spinning out from upstream or downstream industries and entering a focal industry, the knowledge transmitted that passes through industry boundaries is application knowledge for downstream spinouts and technological knowledge for upstream spinouts.

By combining the aforementioned arguments, we can advance the first proposition to be tested empirically:

> **Proposition I - Position in inter-sectoral knowledge space:** *Industries more central in the inter-sectoral knowledge space perform at the international level better than industries that are not central.*

Rethinking centrality in a knowledge space as a composite measure of innovativeness, we can appreciate the moderating effect of learning by being exposed to knowledge flows. As a matter of fact, the greater the amount of information passing through a certain node, the greater will be the capacity of that node to retain and process knowledge flows. Such learning channels may well be captured by degree centrality and local clustering. As we will discuss in depth in the methodological section below, degree centrality and local clustering measure how likely a node ends up being susceptible to all kind of information running through the network, giving us the possibility to measure its "skills" as a recipient of technological flows. Summing up, the centrality of industries in the inter-sectoral knowldge space allows us to capture several possible mechanisms through which technology flows can boost international competitiveness. To some extent, either too much or to little proximity may result detrimental to innovativeness and effective learning (Boschma, 2005). On the one hand, a larger learning basin lead to a wider set of opportunities (superior technologies, innovative products, cost reductions, diffusion of best practices). However, such advantages take place if and only if there are sufficient strong linkages to support knowledge transfer. All told, using network position as a proxy for a richer set of opportunities and capabilities, we can try to incorporate them into our model.

3.2 Geographical Boundaries

In this paper, we propose that not only the position in the the knowledge space, but also the geographical boundaries matter in the inter-sectoral flows of knowledge. We argue that the effects of inter-sectoral knowledge flows on international competitiveness are more relevant at the country level due to the geographical boundaries that affect knowledge flows. In a nutshell, the agglomeration literature posits that knowledge spillovers have clear geographical reach and they are subject to a significant spatial decay. The diffusion of tacit knowledge, to some extent, requires close and frequent interactions, i.e. geographical proximity (Lissoni and Miguelez, 2014). The geographical concentration of people and jobs enhances a rapid and effective spread of tacit knowledge, resulting in a boon for innovative activities. Although the specific mechanism behind such knowledge transfer is not completely disentangled, there is nowadays substantial empirical evidence confirming the localized nature of knowledge diffusion (Arzaghi and Henderson, 2008; Rosenthal and Strange, 2003; Audretsch and Feldman, 1996; Adams and Jaffe, 1996; Carlino and Kerr, 2015). Here we present two different possible explanations on why “local” knowledge flows are expected to be more effective in sustaining competitiveness.

Localized Knowledge Flows. First, effective mechanisms of knowledge exchange require close interactions, frequent meetings and development of trust among economic agents. Within this framework, spatial proximity boosts the flow of ideas by sharply reducing the cost of trading knowledge, enhancing skilled worker mobility and providing better conditions for cooperation among among firms and individuals (Breschi and Lissoni, 2001a). Hence, localized flows are relatively richer of easily exploitable ideas. Further, contrarily to codified knowledge, the diffusion of tacit knowledge might be seriously affected by proximity, which enhance shared routines, similar technology attitudes and trust (Bathelt et al., 2004). Since the first tests on the role of spatial proximity in fostering scientific collaborations (see e.g. Jaffe et al., 1993), the economic geography literature has largely extended the line of research concerning the geographical breath of knowledge flows and their features (Carlino and Kerr, 2015). More in detail, inventors are not very likely to relocate in space and their (bounded) mobility - as well as their co-invention networks - circumscribe the geographical diffusion of knowledge (Singh, 2005; Breschi and Lissoni, 2009; Sonmez, 2017). One of the emerging results suggests that national-scale interactions allow for a more effective transmission and exchange of tacit knowledge than on broader scale. For example, so-called Jacob externalities may result more effective at national or regional level, where the heterogeneity in the composition of the knowledge base can be managed more easily and flows integrated at a lower absorption cost (Antonelli et al., 2017). Indeed, in their review of the literature, Breschi and Lissoni (2001b) underline that although there is variety of mechanisms behind the spread of ideas and expertise, such a diffusion remains, however, largely bounded in space even though exact co-location might not be essential (see also Gallaud and Torre, 2005; Torre, 2008). Moreover, inventor mobility and co-invention networks have been proved to account for a large francion of the spatial proxinty of knowledge diffusion

"National Institutions and Home Market Effect". Basically, the idea is that a country's domestic market may act as a supportive and protective environment for new products, then ready to be successfully exported to foreign markets. The product-life cycle model, introduced by Vernon (1966), supports the idea that geographical proximity is conducive to innovative activities due to the ease of communication and that, at least at the beginning of the product-life cycle, domestic market matters, providing easier, faster and more complete access to information and knowledge. Country's domestic markets can be thought as a space serving as "nurturing grounds" for new products (Linder, 1961; Hirschman, 1958; and more recently, Diodato et al., 2018 and Li et al., 2018). Hence, if national-level institutions matter in such a process by facilitating the flows of knowledge (see also Gittelman, 2006), it is reasonable to argue that they will be also more helpful to innovation and trade than international ones (Laursen and Drejer, 1999). In addition, the literature on national systems of innovation has frequently emphasized the pivotal role of within country knowledge flows and of national institutions as determinant of economic performances (Lundvall, 1988, 1992).

On the basis of these mechanisms we conjecture, in our second proposition, that a central position is still important but less relevant at the international level, where knowledge flows are more codified and available to all countries and competitors.

Proposition II - Geographical boundaries of inter-sectoral knowledge flows: *The position of an industry in the inter-sectoral knowledge space is more relevant at national level than at the international level.*

To summarize, a variety of mechanisms point to the fact that knowledge flows suffer from geographical boundaries. Both knowledge production and diffusion entail a local dimension linked to the easier interaction of different actors. Further, part of the literature supports the idea that the national dimension matters, due to role of common institutions and a relatively more supportive market. Building on such premises, we conjecture that industries benefit more from their position in their national knowledge network rather than the one they have in the international space.

4 Data and Methodology

4.1 Our Data

The empirical analysis of this paper is based on two main sources of data: the ICRIOS-PatStat database and the STAN database (OECD). The STAN database for industry analysis provides comprehensive information to investigate industry performance across countries. The ICRIOS-PatStat contains the full set of bibliographic variables for patents applied at EPO and USPTO (Coffano and Tarasconi, 2014)[9].

More in detail, for patents we consider all the applications with priority date in the time

[9]PatStat (i.e. EPO Worldwide PATent STATistical Database) is a single patent statistics raw database, held by the European Patent Office (EPO) and developed in cooperation with the World Intellectual Property Organisation (WIPO), the OECD and Eurostat.

interval 1995-2009. By merging and elaborating the aforementioned inputs, we obtain a dataset that includes information about 14 manufacturing industries in 16 OECD countries for 15 years[10]. A similar approach has been used in order to collect citation data. The following tables (3 and 4) and figures (1 and 2) provide a more quantitative and exhaustive description of our data and our industry classification based on ISIC3 codes[11].

[Table 1 about here.]

[Table 2 about here.]

[Figure 1 about here.]

[Figure 2 about here.]

4.2 Knowledge Flows and the Network of Industries

The approach used in this paper basically follows a two steps procedure. The first step consists in mapping technology flows among the 14 industries included in our dataset. Taking into consideration the empirical evidence in Laursen and Meliciani (2002, 2010), we consider both national and international knowledge flows. Consequently, we distinguish between the national and the international dimension of the flows. In order to do so, we obtain two sets of symmetrical matrices that will constitute the adjacency matrices for our networks. This methodology represents the framework to construct a national and an international technology space in the form of a network. Such networks provide a representation of inter-sectoral relationships and a characterization of industries' position in our space of knowledge flows. Moreover, this framework allows us to eventually capture the relative centrality of industries. The network representation of a knowledge space has been adopted by Kogler et al. (2013) and Boschma et al. (2014) in order to link technological sectors according to their relatedness. Yet, the goal of our analysis is to capture flows.

The main source of information is given by patent classification codes. As we explain later in this section, relying on classification codes has a number of advantages with respect to

[10] The timespan for which we collected and analyzed the data stops in 2009. Such choice is driven by the occurrence of the Great Recession, that severely affected all the OECD countries in our dataset.

[11] For compatibility reasons our classification is based on ISIC3 codes. The initial NACE2 classification has been converted into ISIC3 by means of standard conversion tables.

patent citations (Joo and Kim, 2009). However, some methodological issues arise in capturing international flows. We aim to overcome technical difficulties by approximating such relationships through a patent citation network (Verspagen, 1997b; Jaffe and Trajtenberg, 2002).

Following the methodology employed in Engelsman and van Raan (1994) and Breschi et al. (2003), we can perform a co-classification analysis based on co-occurrences according to our classification of industrial sectors[12] As pointed out by Breschi et al. (2003), Hinze et al. (1997) and several other WIPO documents, main and supplementary IPC codes cannot be used to disentangle knowledge-producing and knowledge-incorporating sectors. Hence, contrary to Verspagen (1997a,b) we do not infer anything about the direction of the flows. Our purpose is simply to map technological relationships among industrial sectors regardless of formal spillover effects.

Our choice of using co-occurrences based on patent classification codes (with respect to patent citations) derives from several methodological considerations. Patent citations provide a great source of information, although it has been shown that they present several drawbacks in certain applications. For instance, citations are a fully reliable measure in scientific academic settings. Indeed, Joo and Kim (2009) clearly state that the channels through which classification and citations are generated may lead to substantial differences. Alcacer and Gittelman (2006) show how citations added by patent examiners generate noise in the data resulting in a relevant measurement error. Conversely, IPC codes are carefully assigned by patent examiners of the issuing office in accordance to strict WIPO requirements. Leydesdorff (2008); Cockburn et al. (2002) and Criscuolo and Verspagen (2008) argue that citations are subject to authors and examiners choices and that may be the result of legal and strategic factors (Meyer, 2000). Finally, Breschi et al. (2003) show that citations do not add any relevant information to track simple technology flows.

Unfortunately, co-classification is not feasible for examining international technology flows since available information does not allow us to fully disentangle industry classes for couples of countries and industries. As a result, we need to rely on patent citations[13]. Notwithstanding all

[12]From patent data we match technology classes (IPC) with industry classes (ISIC3). In particular, we rely on the information on the NACE code associated to patents from the PatStat database (see Van Looy et al., 2015 for the conversion table IPC-NACE2) and then use the EUROSTAT RAMON coversion tables to move from NACE to the desired ISIC classification employed by the OECD STAN database.

[13]Investigations of citation patterns in our dataset show a clear tendency of a country-specific dimension. See Figure A2 in the appendix.

the shortcomings outlined above, patent citations provide a good approximation for a measure of knowledge flows among industries of different countries (Jaffe and Trajtenberg, 2002, 1999; Verspagen, 1997b). EPO and USPTO data which are, indeed, sufficiently complete to have a good coverage of innovative activities for all countries that we take into consideration (Joo and Kim, 2009). For all these reasons, we believe that our approach to map knowledge flows across industries is the most suitable in this specific application[14].

Summing up, the first step of our methodological approach is essentially driven by two factors: the superiority of co-classification analysis in mapping technology flows across sectors and the impossibility to replicate the exact procedure for international relationships. However, for completeness we perform a robustness check using citation data for both national and international flows. The results can be found in Table 6 and prove that citations can eventually represent a good approximation of international knowledge flows.

In what follows, we formally describe our procedure to build a national knowledge space. We apply an almost identical methodology in order to construct a citation network to control for international relationships.

Let $\mathcal{A}$ be the set of all patent applications. Then, $\mathcal{A}_{ct} \subset \mathcal{A}$ is the set of all patent applications for a given country c at a certain point in time t[15]. Each $a_{ct} \in \mathcal{A}_{ct}$ has been assigned to one or more industry class. Let $P_{ia_{ct}}$be a function such that

$$P_{ia_{ct}} = \begin{cases} 1 & \text{if } a_{ct} \text{ has been assigned to industry } i \\ 0 & \text{otherwise} \end{cases}$$

with $i \in \{A, \ldots, P\} \equiv \mathcal{I}$. Thus, for each country c at time t, the total number of patent applications that has been assigned to code $i \in \mathcal{I}$ can be written as $T_{ict} = \sum_{a_{ct} \in \mathcal{A}_{ct}} P_{ia_{ct}}$; while the total number of patent applications classified in both industrial sectors i and j is simply given by $C_{ijct} = \sum_{a_{ct} \in \mathcal{A}_{ct}} P_{ia_{ct}} P_{ja_{ct}}$. By repeating the count for every pairs of possible industry codes, we obtain a symmetric co-occurrences matrix $\mathbf{C}_{ct}$, of dimension (14×14), for every country at

[14] The distinction between national and international measures is not a matter of differences among countries/industries, it rather concerns the nature of co-occurrence and citation data. Using co-occurrences, we are not able to disentangle, and thus to count in a meaningful way, every IPC-country link. We overcome such difficulty by relying on citations, which include, in a way, an additional layer of information to map within-country industry relationships as well as across-country industry linkages.

[15] $c \in \{AT, \ldots, US\} \equiv \mathcal{C}$ and $t \in \{1995, \ldots, 2009\} \equiv \mathcal{T}$

each point in time.

We consider such matrices as adjacency matrices of our networks. That is, $\mathbf{C}_{ct}$ formally defines a network of inter-sectoral relationships among industries for country c at time t. We use the notation $\Gamma_{ct} = (\mathcal{I}, \mathcal{L})$ where $\mathcal{I} = \{A, \ldots, P\}$ is the set of nodes and $\mathcal{L} \subseteq \mathcal{I} \times \mathcal{I}$ is the set of links.

As long as we consider a weighted network, the matrix representation takes the following form:

$$\mathbf{c}_{ct} = \begin{cases} C_{ijct} & \text{if } (i,\, j) \in \mathcal{L} \\ 0 & \text{Otherwise} \end{cases}$$

with $C_{ijct} \in \mathbb{N}_{+}$. Figure 3 is an illustrative example of networks derived through the above mentioned procedure and describes the national (Italian) and international knowledge space in 2009. More in detail, in (a) nodes' sizes are set according to the degree centrality and links' widths are proportional to weights C_{ijct}. In (b) the entire space - aggregated by country - is mapped to visualize international connections, within-country relationships are empathized. In the next sections, we derive more insightful network measures and we rely on such measures to construct the econometric strategy of the paper.

[Figure 3 about here.]

4.3 Variables & Descriptive Statistics

The variables used in order to study the relationship between the competitiveness of industries and their position in our knowledge space are summarized in Table 1.

As a general measure of international competitiveness we consider export market shares (XMS). Such measure is derived by taking into account country's exports in a given industry (current dollars) over the total industry's exports from all countries included in our dataset. The choice of some regressors follows Dosi et al. (2015). More in detail, tech-related variables are represented by Patent-share (PATSH) and Investments (INV). Patent-share captures the share of national industry patent applications (USPTO and EPO) over the total industry's patent applications of all countries in the dataset. Investments is defined as the ratio between industry expenditures on gross fixed capital formation and value added (current prices). Moreover, we include in the analysis a price-related variable: Labor-cost-per-employee (WAGE). Total population (POP) controls for possible size effects.

The impact of industries' position in our knowledge space captures the inter-sectoral diffusion of advanced knowledge. Several measures of centrality have been developed in order to capture different features of the network structure and identify key players. Here it is necessary to briefly review the most important ones. Freeman (1978) formalizes three different basic measures of centrality: degree, closeness and betweenness. The most direct measure of popularity is the degree centrality, which is defined as the number of links a node has in the network. It can be interpreted in terms of the immediate risk of a given node for catching whatever is flowing through the network. Instead, closeness centrality is defined as the inverse sum of shortest paths to all other nodes from a given node in the network and it measures whether a node is in the position of reaching information quickly. Betweenness centrality is defined as the geodesic path that passes through a given node and it captures the property of controlling information flows within a given graph. Therefore, it can be used to identify who plays the role of a broker or a gatekeeper. As Burt (2004) points out, such bridging position can represent power and can be associated with consistent advantages since knowledge and information must pass through such nodes. Finally, Bonacich (1987) develops a more sophisticated measure to evaluate the most influential nodes which is called Eigenvector centrality. Such measure assigns different weights to links according to the relative influence of a node and it has been widely applied in the literature to assess power, the structure of inter-organizational networks and the role of an individual or an entity in a general social network.

The local clustering coefficient of a node in a network is used to quantify how connected its neighbors are and whether they form a clique (complete graph) or not. Watts and Strogatz (1998) in their seminal paper constructed a model that accounts for both local clustering and small-world property of networks. Despite most of such measures have been initially developed for binary networks, they can easily be generalized for weighted networks (Opsahl et al., 2010; Barrat et al., 2004). For our purpose, we choose two simple network measures for both networks (co-occurrences and citations): the weighted degree centrality and the local clustering coefficient[16].

Formally, we can define weighted degree centrality for a network $\Gamma = (\mathcal{I}, \mathcal{L})$ as follows:

[16] For completeness, in the appendix we include the unweighted degree centrality and the eigenvector centrality.

$$d.w_i = \sum_{j \in \mathcal{I}} C_{ij} \tag{2}$$

Such simple measure captures network centrality in a direct and immediate fashion (Borgatti, 2005). Indeed, weighted degree can be interpreted as the opportunity to influence as well as be influenced directly. As a result, central actors are more likely to be exposed to what is flowing through the network, in this specific case knowledge.

For what concerns the local clustering coefficient, we use the generalization for weighted networks proposed by Barrat et al. (2004). The analytical expression in which we removed the dependence from time to ease notation, reads as follows:

$$am_i = \frac{1}{d.w_i(k_i - 1)} \sum_{j,h} \frac{C_{ij} + C_i h}{2} \xi_{ij} \xi_{ih} \xi_{jh}, \tag{3}$$

where k_i is the number of industries linked to i and ξ_{ij} is an indicator function that takes value 1 if industry i is linked to j and 0 otherwise. This coefficient is a measure of the local cohesiveness that takes into account the importance of the clustered structure on the basis of the amount of interaction intensity actually found on the local triplets. Indeed, am_i counts, for each triplet formed in the neighborhood of the vertex i, the weight of the two participating edges of i. Using this measure we are considering not just the number of closed triplets in the neighborhood of a vertex but also their total relative weight with respect to the strength of the vertex. The normalization factor $d.w_i(k_i - 1)$ accounts for the weight of each edge times the maximum possible number of triplets in which it may participate, and it ensures that the local clustering coefficient always falls between 0 and 1.

Within this setting the neighborhood of a node can play a crucial role. Even if an industry would result not particularly central according to the weighted degree, it might belong to a clique and such embedness in the network can guarantee a competitive advantage anyway. Therefore, the weighted local clustering coefficient helps us to eventually capture the impact of such connectiveness.

By looking at Table 5 below we can observe how the two network measures correlate with our baseline variables through a cross-correlation matrix. For instance, at national level we can notice how weighted degree ($d.w$) is positively associated with both export market share and

Table 1: Variables

Var. Name	Description	Data Source
XMS	Country's exports in the industry over the total industry's export	OECD-STAN
INV	Ratio between industry expenditures on gross fixed capital formation and value added (current prices)	OECD-STAN
WAGE	Labour cost per employee	OECD-STAN
POP	Total population	OECD-STAN
PATSH	Share of national industry patents applications over the sum of the industry's patents applications	CRIOS-PatStat
d.w	Degree centrality (technological class co-occurrence network)	CRIOS-PatStat
ev	Eigenvector centrality (technological class co-occurrence network)	CRIOS-PatStat
am	Local clustering (technological class co-occurrence network)	CRIOS-PatStat
d.w.cit	Degree centrality (citation network)	CRIOS-PatStat
ev.cit	Eigenvector centrality (citation network)	CRIOS-PatStat
am.cit	Local clustering (citation network)	CRIOS-PatStat

patent share. Such positive relationship holds for local clustering (*am*) as well. We will focus on the two network measures described above for all the aforementioned reasons, although some alternative specification are summarized in the appendix (Table A1).

[Table 3 about here.]

Moreover, to describe the relative position of industries in a national knowledge space, Figure 4 compares how industries in Italy in 2009 are ranked according to our network measures. It captures the possible heterogeneity in terms of centrality and local clustering among industries. The closer two triangles are in the plot, the bigger is the "difference" in terms of degree and clustering for a given industry. For instance, sector A (i.e., Food, Beverage and Tobacco) has a relative low degree but its embedded into a well connected cluster. Finally, Figure 5 describes the evolution over time of our network measures in Italy.

[Figure 4 about here.]

[Figure 5 about here.]

In the next sections, we will investigate whether the network structure and the relative position of industries - as indicated by centrality and local clustering - in the space of knowledge flows is positively associated to export performances. Of course, beyond the national network of industries we also take into account international relationships (Laursen and Meliciani, 2002, 2010). As mentioned above, given the impossibility of using co-occurrence information, we characterize the latter dimension relying on patent citations.

5 Econometric Strategy

In this paper we use two different econometric specifications. First, we follow Dosi et al. (2015) in exploring the link between export market shares and both technological and cost factors in a standard panel framework, with the obvious difference that we do not estimate the model in each industry separately because we are interested in inter-sectoral knowledge linkages. Secondly, once we have underlined the high persistence of export market shares over time, we move to a dynamic model with an autoregressive structure in the dependent variable akin to Amendola et al. (1993) and Laursen and Meliciani (2002). Both the two specifications may also have an evolutionary interpretation as specifying the selection dynamics linking "fitness" and expansions or contractions of export shares at the sectoral level. When a country is better in terms of cost and technology competitiveness relatively to its counterparts, it will increase its exports more than the counterparts. Fitness is captured both by cost competitiveness and technological features, notably including the relative position of each industry in the network of knowledge flows. This view also helps justify the choice of our dependent variable. Moreover, as reported in Laursen and Meliciani (2010), from an econometric point of view, exports normally grow over time (as world income does) and a variable measuring exports in absolute terms is very likely to be non-stationary. By contrast, an export market share variable is much more likely to be stationary, at least in the first moment.

The baseline model, from which we obtain the different specifications estimated in the paper, is:

$$\begin{aligned} XMS_{ijt} &= \alpha_0 + \gamma XMS_{ijt-1} + \alpha_1 PATSH_{ijt} + \alpha_2 WAGE_{ijt} + \alpha_3 INV_{ij} + \\ &+ \alpha_4 POP_{ijt} + \beta_1 d.w_{ijt} + \beta_2 am_{ijt} + \beta_3 d.w.cit_{ijt} + \beta_4 am.cit_{ijt} + \\ &+ \eta_{1i} + \eta_{2j} + \eta_{3t} + \epsilon_{ijt}, \end{aligned} \tag{4}$$

where the coefficients α_h are associated to the standard control variables, β_h capture the effects of industries' positions in the inter-sectoral knowledge network and η_h represent different kinds of fixed effects we control for. Moreover, in many specifications we introduce the interaction effect between our network centrality and local clustering measures, for the national or international networks. This allows us to test whether, for an industry, the importance of being in a central position with respect to the flows of knowledge diminishes as long as it becomes more and more embedded in a tied cluster. All the variables, with exception of fixed effect dummies, are in logarithms and vary in the cross-sector, cross-country and cross-time dimensions. When an estimated coefficient in our model obtains a positive sign (as we expect in the majority of cases) this implies that when the country increases (decreases) its relative technology (knowledge flows, investment, etc.) in a given industry, the country increases (decreases) its market share in that industry. As it is standard in the literature, we expect unit labor costs to have a negative impact on export share dynamics (although this effect could be null considering that the dependent variable is expressed in current prices), while technology variables to have a positive effect on export share. The novelty of the paper consists in the analysis of the role of technological factors in sustaining international competitiveness, with a particular emphasis on the effects driven by industries' position in the networks of knowledge flows and distinguishing between national and international flows.

The estimation strategy we adopt clearly differs in the case we test a dynamic model with an autoregressive component or we remain with the baseline model proposed in Dosi et al. (2015), which is simply obtained imposing $\gamma = 0$. When estimating the specification that does not consider an autoregressive element we start by pooling OLS with sector, year and country dummies. However, as it is well known, the presence of unobserved heterogeneity possibly correlated with other regressors makes our estimates biased and inconsistent; furthermore, the number of cross-sectional observations in our sample is rather restricted. To attenuate these two problems, and considering that our main variables of interest have been shown in section 4.3 to vary, often considerably, over time, we estimate our model using a Fixed Effect (FE) within estimator.

Of course we know that failing of the strict exogeneity assumption would make our FE estimator inconsistent. In our context, in particular, the presence of a dynamic structure in the true data generating process is likely (Amendola et al., 1993; Laursen and Meliciani, 2002, 2010). This would imply some degree of persistence in the competitiveness of industries, suggesting that path dependence might play a non trivial role. Moreover, as a rough observation, we report that unconditional correlation between XMS and its first and second lags is relatively high (see Table 5). Since we use a within estimator, in presence of long enough samples, the asymptotic bias we might incur in is well known to converge to zero under suitable stability conditions. However, we only have $T = 14$ periods, which make it difficult to argue in favor of a sufficiently small bias. To account both for an autoregressive component in our model specification and to solve the presence of such a negative bias (under the assumption that $\gamma > 0$) affecting the within estimator, we move to a different strategy. In particular, we use the Blundell-Bond (BB) Generalised Method of Moments (GMM) estimator, which gives consistent estimates provided that there is no second order serial correlation among the errors, and we report tests for first and second order autocorrelation. This BB-GMM specification is preferred to the original Arellano and Bond estimator due to the high persistence in the series (see discussion in Blundell and Bond, 1998 and Laursen and Meliciani, 2010). We assume, as it is standard in this literature, exogeneity of all explanatory variables. The exogeneity of relative prices is a common hypothesis in estimating export equations and is based on the idea that the export supply price elasticities facing any individual country are infinite. Technology variables are assumed to be exogenous since they should capture structural characteristics that may respond only very slowly to changes in export shares.

6 Results

Our propositions have been confirmed by the empirical analysis. Indeed, results support both conjectures concerning the centrality of industries in the inter-sectoral knowledge space as well as the greater role of the national dimension of technological flows. Our empirical strategies (pooled OLS/FE and GMM) coherently show that centrality and clustering in the national network positively associate with export market shares, the effects are significant and the interaction term displays a negative sign.

More in detail, table 2 presents the estimates of both pooled and FE model specifications, taking into account national (columns 1-2) and international (columns 3-4) boundaries. Interestingly, including both geographical dimensions (columns 5-6), centrality measures, operationalized by means of weighted degree and local clustering, appear to positively and significantly explain export performances. Furthermore, only national-wise measures yield significant estimates, maintaining the existence of geographical boundaries to the diffusion of knowledge flows. The negative sign of the interaction term between the two network measures, instead, provides support for our intuition: being central in a knowledge space is far less relevant when the industry is highly connected within a cluster. Such estimates remain robust after including country, industries and year dummies.

As mentioned in the previous section, despite being informative, static models fail to ensure unbiased estimates within this setting due to persistence in industries' export performances. To overcome methodological difficulties, we chose to employ the dynamic panel estimator (a.k.a. Blundell-Bond estimator), introduced in section 5. Estimation results obtained using a model with an autoregressive component are collected in Table 6. The first two columns refer to national and international baseline model specifications. Both our propositions are robustly confirmed, even within the dynamic setting with time dummy included. However a remarkable difference applies. When the persistent nature of export performance is conveniently taken into account (i.e. including lags), it emerges that the effect of technological variables is captured by industry's relative position in the national network of knowledge flows, which is expressed through its centrality and local clustering, and by persistence in export performances, while the effects of patenting activities is not significant anymore. Such evidence points to the usefulness of our approach in capturing relevant information concerning knowledge generation and diffusion.

The redundancy of being central and well locally-clustered is confirmed and, further, we find that when both national and international network measures are included (column 2), just the former produce a significant effect on competitiveness. However, it is worth recalling that they are constructed using different data sources (IPC co-occurrence vs. patent citations), which might make the two set of regressors not fully comparable. To tackle such an issue, we have run a robustness check (columns I and II) using citations to construct both the national and international knowledge space[17]. The standardization of network measures' derivation, while dispelling any operational concerns, does not alter results, which remain fairly robust. Additional robustness checks in a static setting, related to the choice of a different centrality measure, can be found in the Appendix. The Arellano-Bond test for autocorrelation is performed and reported for each and every specification as well as Hansen-Sargan for the validity of the instruments. As a matter of fact, centrality measures as well as their interaction keep behaving as expected.

Our network approach, however fairly simple, has proven particularly useful to conclude that centrality plays a crucial role in explaining industries' export performances and that geographical proximity is a firm moderating factor.

[Table 4 about here.]

[17]Figure A1 in the appendix shows how our measures (including the ones derived from national citation networks) correlate with each other.

Table 2: Regression Results for Model without Autoregressive Component

	Dependent variable: XMS					
	National (Co-occurrences)		International (Citations)		Final (Co-occurrences and citations)	
	(pooled)	(FE)	(pooled)	(FE)	(pooled)	(FE)
PATSH	0.071***	0.387***	0.074***	0.350***	0.064***	0.350***
	(0.021)	(0.068)	(0.021)	(0.067)	(0.021)	(0.070)
WAGE	0.016***	0.010*	0.013***	0.008	0.014***	0.008
	(0.004)	(0.005)	(0.003)	(0.005)	(0.003)	(0.005)
INV	0.046***	0.029***	0.047***	0.030***	0.045***	0.028***
	(0.008)	(0.008)	(0.008)	(0.008)	(0.008)	(0.008)
POP	−0.058*	0.002	−0.033	0.014	−0.049	0.007
	(0.032)	(0.029)	(0.032)	(0.028)	(0.032)	(0.029)
d.w	0.018***	0.013**			0.012**	0.010*
	(0.006)	(0.005)			(0.006)	(0.005)
am	0.076***	0.062**			0.076***	0.061**
	(0.029)	(0.027)			(0.029)	(0.027)
d.w.cit			0.018	0.026*	0.005	0.021
			(0.011)	(0.014)	(0.013)	(0.017)
am.cit			0.014	0.153	−0.103	0.089
			(0.116)	(0.130)	(0.141)	(0.168)
d.w:am	−0.015*	−0.014*			−0.014*	−0.014*
	(0.008)	(0.008)			(0.008)	(0.008)
d.w.cit:am.cit			−0.017	−0.031	0.0005	−0.022
			(0.017)	(0.021)	(0.019)	(0.025)
Country dummies	Yes	Yes	Yes	Yes	Yes	Yes
Industry dummies	Yes	Yes	Yes	Yes	Yes	Yes
Year dummies	Yes	Yes	Yes	Yes	Yes	Yes
Observations	2,778	2,778	2,811	2,811	2,778	2,778
R^2	0.561	0.379	0.561	0.385	0.563	0.381
Adjusted R^2	0.551	0.347	0.551	0.353	0.553	0.349
F Statistic	69.796***	73.933***	71.934***	76.847***	67.627***	65.271***
	(df = 50; 2727)	(df = 21; 2546)	(df = 49; 2761)	(df = 21; 2579)	(df = 52; 2725)	(df = 24; 2543)

Note: $^{*}p<0.1$; $^{**}p<0.05$; $^{***}p<0.01$

7 Discussion and Conclusions

This paper proposes a novel factor that affects the international competitiveness of industries: the position of an industry in the inter-sectoral knowledge space. The recent literature has suggested that innovation and technological change are more relevant than cost-related factors in explaining industries' competitiveness, coherently with the interpretation of trade as a partial-disequilibrium process where heterogeneous firms compete, innovate, specialize and transfer knowledge across time and space in an imperfect and often unpredictable manner. In such a context, the impact of cost-based factors is limited. This paper adds to stream of contributions suggesting that innovation, R&D activities and the stock of knowledge are relevant determinant of competitive advantage (Dosi et al., 2015; Laursen and Meliciani, 2000, 2002, 2010); beyond such indicators of innovation stock, we find that the position of industries within the inter-sectoral flows of knowledge matters. From our estimates, it is not the innovative effort of an industry or the direct knowledge links among industries that affect international competitiveness when the position within the inter-sectoral knowledge flow is accounted for. Rather, industry's performance is robustly and positively affected by the being central and locally well connected to other industries' knowledge stocks. Notably, our results suggest that competitive advantage positively relates to the position of an industry in the national (rather than international) knowledge space: being conveniently located within the streams of knowledge generated within the country matters more than being so in the whole knwoledge space.

Shortly, we find that (i) industries that are more central in the inter-sectoral knowledge space of their respective countries outperform their foreign competitors and that (ii) the relevant geographical dimension in determining such an effect is the national one. To obtain such results we have combined the use of firm level patent data - which have been duly aggregated into sectoral variables - and industry - level data on exports and costs for a set of 16 OECD economies over a time span of 15 years (1995-2009). Results from our regressions robustly confirm that trade performance is positively affected by network measures characterizing the position of industries in the knowledge space. In particular, being either central or clustered in the network of knowledge flows (the knowledge space) significantly boost export market shares. However, these two effects are found to be redundant: being central in a knowledge space is far less relevant when the industry is highly connected within a cluster. Interestingly, such effects almost completely capture the role of industries' innovativeness, which turns out not to be significant when our network measures are included in the model (see tables 2, 6). It must be emphasized that we do not claim that innovation activities per se are not important in explaining trade competitiveness of industries; rather, we point out that with respect to knowledge and innovation, our approach leads to develop a variable which is more informative than the patent share of an industry, which completely neglects inter-sectoral flows of knowledge. In addition, our second proposition finds confirmation in the results which suggest that the most relevant network for an industry - i.e. the network where being central matters - is the one of national knowledge flows. We also provide some possible explanations regarding the role of the inter-sectoral knowledge space (see section 3). A first mechanism involves the concept of variety of opportunities (see for example Boschma (2005) and Balland et al. (2015)): being a central industry in the flows of knowledge across industries enlarges its opportunities to innovate and to eventually exploit such innovations on the market. A second mechanism points to recombination (Ferguson and Carnabuci, 2017): if innovation requires the recombination of knowledge, then being exposed to several different technological flows coming from different industries may significantly increase innovativeness and, hence, the possibility to benefit from them in the market. Third, being exposed to a variety of knowledge flows coming from other industries may help an industry to develop technological as well as managerial capabilities to perfectly master different technologies and eventually match them with the industry's application and market context (Christensen et al., 1998; Cohen and Levinthal, 1990). Similarly, regarding the importance of the national dimension of knowledge flows we believe that the localized nature of knowledge flows and the presence of "home market bias" effects (Vernon, 1966; Linder, 1961) offer reasonable explanations for the larger importance of national rather than international connections.

More generally, our claim that industries have direct and indirect knowledge relationships with other industries which positively affect international competitiveness point to a still rather unexplored dimension of innovation and technological change: the various ways in which industries are tied together and affect each other in terms of knowledge, innovation and performance. This can be related to the broader issues of what constitutes an industry knowledge base and which are the various direct and indirect inter-sectoral channels which feed and generate this knowledge base (Breschi et al., 2003; Malerba, 2002; Dosi and Nelson, 2010). In fact, knowledge in an industry does not automatically spills over from its "production" within the industry (Dosi, 1988; Dosi et al., 2015), but it may originate and diffuse in various ways and through various channels from other industries: through vertical linkages (Hirschman, 1958; Lundvall, 1992); tacit knowledge flows (Breschi and Lissoni, 2001a), movement of people and new firms that carry knowledge across industry boundaries (Adams et al., 2018) or broader links and inter-sectoral relationships at the organizational or institutional or organizational level, such as diversification or vertical integration (Helfat and Campo-Rembado, 2016; Li et al., 2018).

All such elements point to interesting areas for future of research. First, it is important to examine in detail and empirically assess the relevance of the various mechanisms proposed in this paper through which inter-sectoral knowledge flows affect the competitiveness of an industry. Second, our analysis is focused only on 14 industries. More disaggregated analysis with more fine grained data is necessary. For instance, regional level data would provide useful information to further investigate to what extent geographical boundaries matter - we only distinguish beetween national versus international flows. Third, the number of countries examined in this paper is limited and focuses on OECD countries. Our reasoning does not necessarily holds for several emerging countries in which some local industries are not developed and therefore are not present.

In conclusion, this paper adds a novel insight to the analysis of export performance of countries and has also interesting implications for public policy. For countries, it is indeed important to promote and raise innovation and R&D in industries. However, we support the idea that they should also foster inter-industry collaborations among firms and links among industries. This second type of policy complements and does not substitute the first one: only industries and firms that are innovative and do R&D are able to benefit from inter-industry knowledge flows and increase their international competitiveness. Finally, geographical boundaries must be taken into account if we want to design effective policies.

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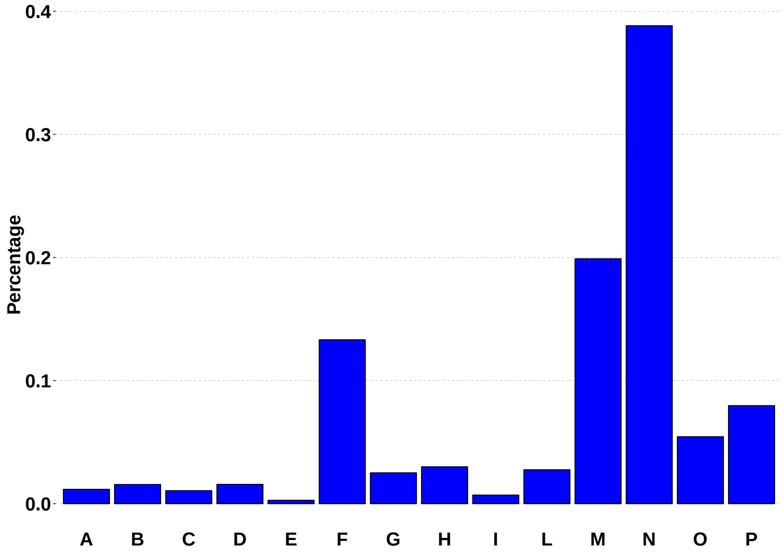
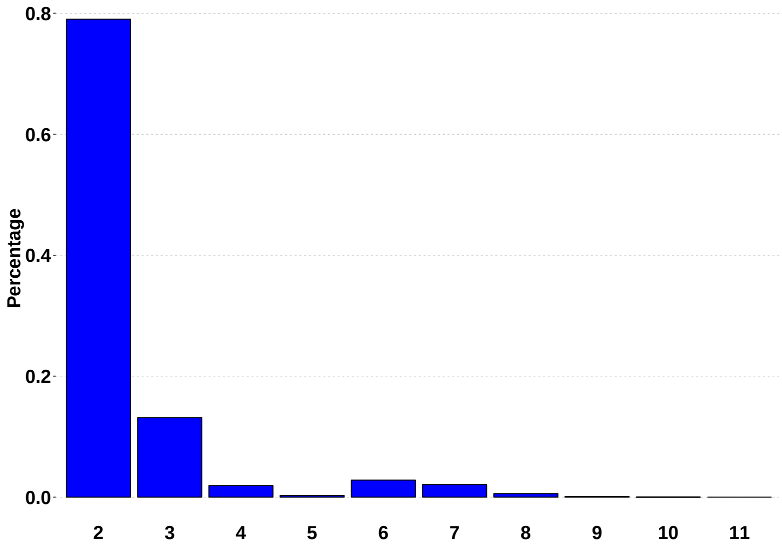
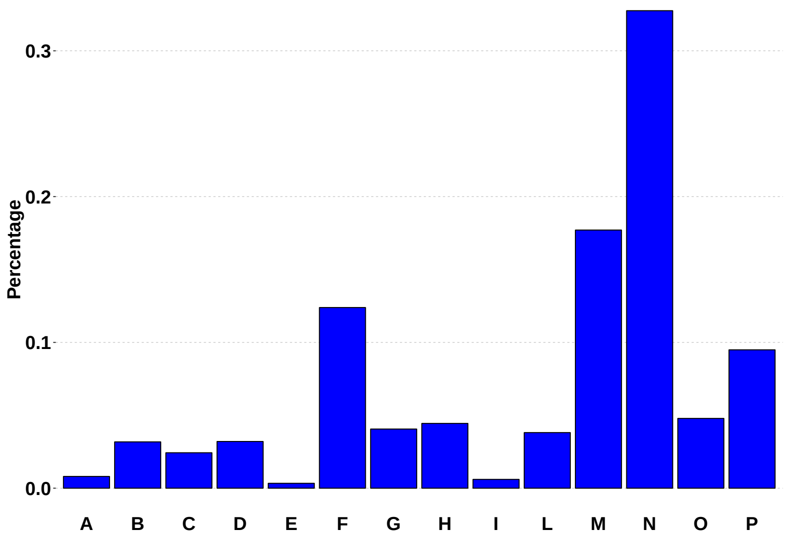


(a) Distribution of Patent Applications by Industry

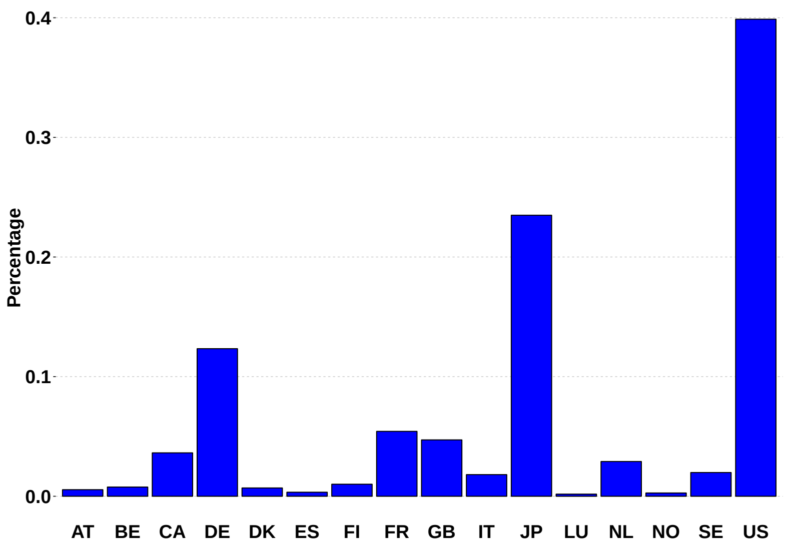


(b) Distribution of Patent Applications by Number of Industries

Figure 1: Patent Applications

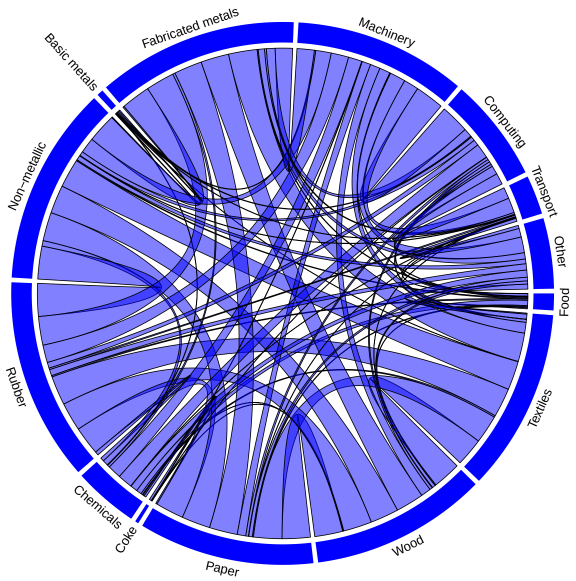


(a) Distribution of Aggregate Citations by Industry

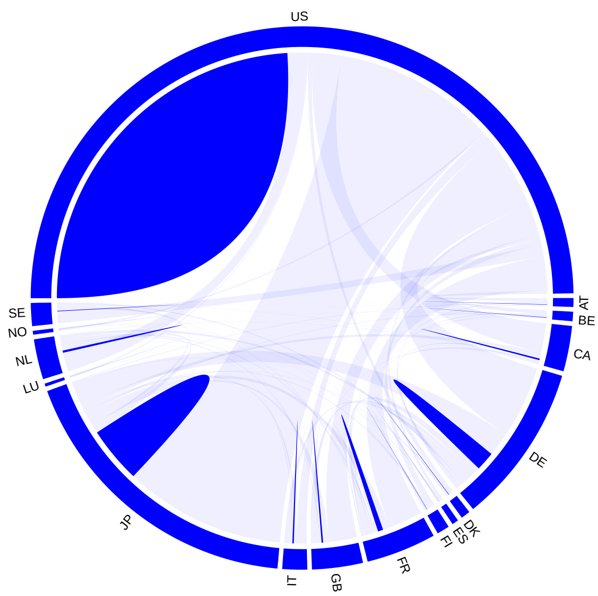


(b) Distribution of Aggregate Citations by Country

Figure 2: Aggregate Citations



(a) 2009 - ITALY



(b) 2009 - By Country

Figure 3: Knowledge Networks based on Patent Data

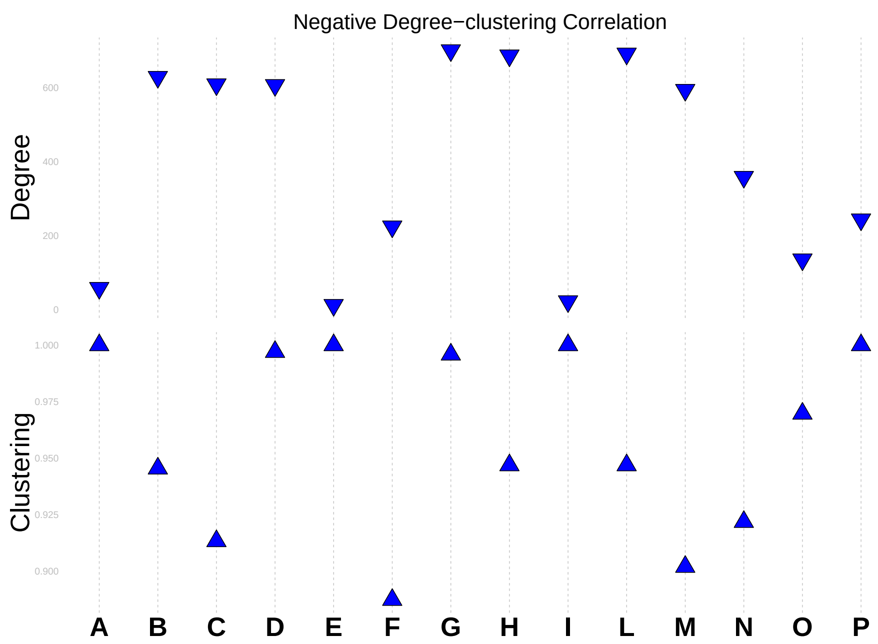


Figure 4: Weighted Degree and Weighted Local Clustering by Industry - ITALY 2009

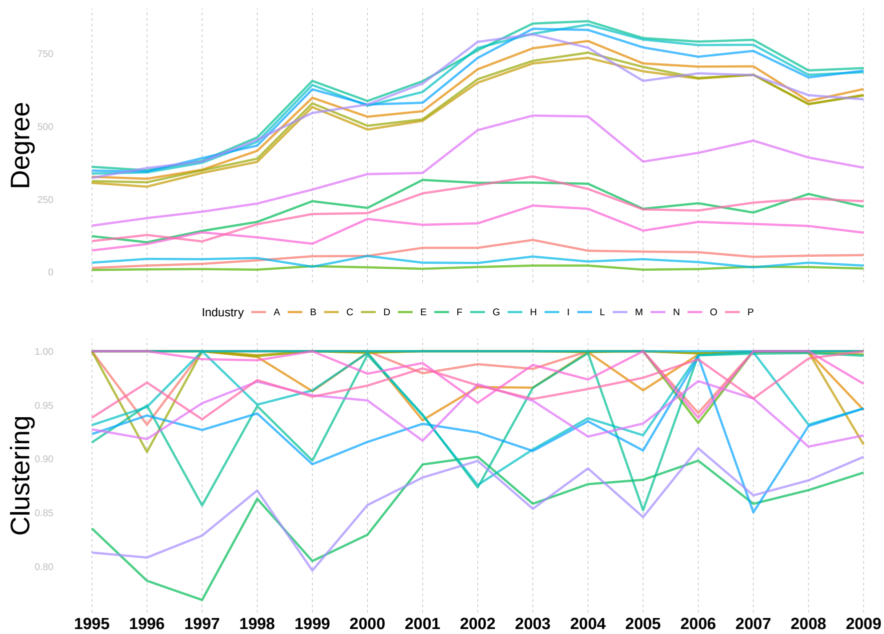


Figure 5: Weighted Degree and Weighted Local Clustering by Industry - ITALY

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Table 3: List of Countries

Country	Code	Country	Code
Austria	AT	United Kingdom	GB
Belgium	BE	Italy	IT
Canada	CA	Japan	JP
Germany	DE	Luxembourg	LU
Denmark	DK	Netherlands	NL
Spain	ES	Norway	NO
Finland	FI	Sweden	SE
France	FR	United States	US

Table 4: Industry Classification

Industry	ISIC3	CODE	APPLICATIONS		CITATIONS	
			%	#	%	#
Food, beverages and tobacco	15-16	A	1,17%	44091	0.80%	437616
Textiles, wearing, leather	17-19	B	1,55%	58900	3,18%	1723416
Wood	20	C	1,05%	39944	2,44%	1318938
Paper and printing	21-22	D	1,57%	59407	3,20%	1737386
Coke	23	E	0.28%	10402	0,33%	181814
Chemicals	24	F	13,31%	504805	12,40%	6720031
Rubber and plastic	25	G	2,50%	94891	4,05%	2200584
Non-metallic (mineral products)	26	H	2,99%	113633	4,45%	2409767
Basic metals	27	I	0.70%	26383	0,60%	328165
Fabricated metals (products)	28	L	2,75%	104441	3,81%	2068636
Machinery	29	M	19,90%	754265	17,70%	9601586
Computing and electrical (machinery)	30-33	N	38,82%	1472210	32,75%	17761391
Transport	34-35	O	5,44%	206271	4,79%	2595884
Other manufacturing	36-37	P	7,97%	301956	9,50%	5147308
Total			100%	3791599	100%	54232522

Notes: If an application (citation) has been assigned to two (or more) industries according to original IPC codes then it is counted twice (or more). The total number of applications (citations) has been derived accordingly.

Table 5: Cross-correlation Matrix

	XMS	PATSH	WAGE	INV	POP	d.w	am	d.w.cit	am.cit
XMS		0.13	0.19	-0.01	0.16	0.13	0.22	0.1	-0.06
PATSH			0.2	-0.16	0.95	0.79	0.22	0.68	-0.28
WAGE				0.09	0.16	0.13	0	0.19	-0.17
INV					-0.14	-0.13	0.01	-0.07	0.03
POP						0.78	0.24	0.67	-0.27
d.w							0.16	0.91	-0.22
am								0.12	0.12
d.w.cit									-0.2
am.cit									

Note: The correlation coefficients between export market shares (XMS) and its first and second lag are respectively: 0.84 and 0.73.

Table 6: Regression Results for Model with Autoregressive Component (Blundell-Bond Estimator)

	Dependent variable: XMS			
	Baseline (Co-occurrences and citations)		Robustness (Citations)	
	(1)	(2)	(I)	(II)
XMS_{-1}	0.956*** (0.027)	0.956*** (0.027)	0.953*** (0.032)	0.954*** (0.031)
XMS_{-2}	−0.028* (0.016)	−0.029* (0.016)	−0.047*** (0.015)	−0.046*** (0.015)
PATSH	−0.002 (0.004)	−0.003 (0.004)	−0.002 (0.005)	−0.004 (0.005)
WAGE	0.0004 (0.001)	0.00005 (0.001)	0.001 (0.001)	0.001 (0.001)
INV	0.001 (0.004)	0.001 (0.004)	0.002 (0.005)	0.001 (0.005)
POP	0.002*** (0.0003)	0.002*** (0.0003)	0.002*** (0.0004)	0.002*** (0.0004)
d.w	0.005** (0.002)	0.004** (0.002)		
am	0.030*** (0.009)	0.029*** (0.009)		
d.w.cit		0.00005 (0.0004)		−0.0004 (0.001)
am.cit		−0.033 (0.026)		−0.030 (0.029)
d.w:am	−0.008*** (0.003)	−0.007** (0.003)		
d.w.cit.control			0.005** (0.002)	0.005** (0.002)
am.cit.control			0.032** (0.012)	0.029** (0.012)
d.w.cit.control:am.cit.control			−0.008** (0.003)	−0.007** (0.003)
Time Dummies	Yes	Yes	Yes	Yes
Observations	2811	2811	2811	2811
AR(order1)	−5.23***	−5.24***	−5.29***	−5.30***
AR(order2)	−1.54	−1.55	−1.01	−1.09
Wald Test (coef.)	7703.89***	8047.81***	6071.79***	6258.51***
Wald Test (int.)	477.00***	486.01***	422.93***	416.08***
Sargan/Hansen (χ^2)	55.02 (df = 100)	55.01 (df = 102)	12.89 (df = 96)	12.94 (df = 98)

Note: *p<0.1; **p<0.05; ***p<0.01. The robust one-step GMM estimator is used. The number of lags used to instrument the endogenous variable go from the fourth onwards.The first two lags of our dependent variable are included in model specification. Time dummies included when specified but coefficients not reported. AR (1) and AR (2) are Arellano-Bond tests that average autocovariance in residuals of respectively order 1 and 2 are zero. Wald tests for intercepts and slopes suggest rejection of homogeneity. Sargan/Hansen accounts fro the validity of the instruments.

A Additional Measures & Figures

The empirical analysis confirmed a prevalent effect of the "National" dimension in a knowledge space. Table A1 summarizes some basic results we obtained using two alternative centrality measures and estimating the corresponding specifications by pooled OLS. In particular, we consider degree centrality (unweighted) and eigenvector centrality. Formally, for a network $\Gamma = (\mathcal{I}, \mathcal{L})$ with adjacency matrix $\mathbf{A}$ whose elements are such that:

$$a_{ij} = \begin{cases} 1 & \text{if } (i, j) \in \mathcal{L} \\ 0 & \text{Otherwise} \end{cases}$$

we can write degree centrality as the number of ties that involve a given node:

$$d_i = \sum_{j \in \mathcal{I}} a_{ij}$$

Furthermore, eigenvector centrality can be written as the principal eigenvector of the adjacency matrix of the network:

$$\lambda \mathbf{v} = \mathbf{A}\mathbf{v}$$

where λ is the eigenvalue and $\mathbf{v}$ the eigenvector. Of course, different centrality measures produce different results since they capture different features of the network (see section 4.3 and Borgatti (2005) for a brief and intuitive description of centrality measures). Nevertheless, we can see that the alternative specifications we use provide insights that go in the same direction of the effects highlighted and discussed in the paper. In particular, both degree and eigenvector centrality at national level are positively associated with export market shares, although in a much less robust way.

Figure A1 summarizes how our network measures correlate with each other. Control variables, used as robustness check (d.w.cit.control and am.cit.control) refer, respectively, to weighted degree and local clustering, computed at the national level but using citations instead of co-occurrences.

[Figure A1 about here.]

Table A1: Alternative Centrality Measures

	Dependent variable: XMS					
	Degree			Eigenvector		
	(National)	(International)	(Final)	(National)	(International)	(Final)
PATSH	0.127***	0.118***	0.118***	0.117***	0.122***	0.115***
	(0.019)	(0.019)	(0.019)	(0.019)	(0.019)	(0.020)
WAGE	0.015***	0.015***	0.014***	0.016***	0.016***	0.015***
	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)
INV	0.053***	0.053***	0.052***	0.050***	0.051***	0.051***
	(0.008)	(0.008)	(0.008)	(0.008)	(0.008)	(0.008)
POP	−0.035	−0.034	−0.035	−0.034	−0.032	−0.033
	(0.032)	(0.032)	(0.032)	(0.032)	(0.032)	(0.032)
d	0.007***		0.003			
	(0.002)		(0.003)			
ev				0.009***		0.009***
				(0.003)		(0.003)
am	0.043***		0.045***	0.033***		0.038***
	(0.013)		(0.013)	(0.013)		(0.013)
d.cit		0.007***	0.006**			
		(0.003)	(0.003)			
ev.cit					0.002	−0.006
					(0.008)	(0.008)
am.cit		−0.073	−0.083		−0.123**	−0.130***
		(0.052)	(0.052)		(0.049)	(0.049)
Observations	2,778	2,778	2,778	2,778	2,778	2,778
R^2	0.556	0.556	0.558	0.556	0.554	0.557
Adjusted R^2	0.546	0.546	0.547	0.546	0.545	0.547
F Statistic	71.163*** (df = 48; 2729)	71.116*** (df = 48; 2729)	68.764*** (df = 50; 2727)	71.140*** (df = 48; 2729)	70.740*** (df = 48; 2729)	68.571*** (df = 50; 2727)

Note: $^{*}p<0.1$; $^{**}p<0.05$; $^{***}p<0.01$

Figure A2 describes two knowledge networks based on patent citations in two different points in time (1995 and 2009). To be as clear as possible, we aggregate data by country and by industry. Edges' colors are set according to intra-industry (intra-country) relationships in order to capture citations' patterns. It's worth noticing that both intra-industry and intra-country links can help us to understand the underline mechanism of network formation. Figure A3:A18 show the "national" knowledge space evolution over time across all countries in our dataset.

[Figure A2 about here.]

[Figure A3 about here.]

[Figure A4 about here.]

[Figure A5 about here.]

[Figure A6 about here.]

[Figure A7 about here.]

[Figure A8 about here.]

[Figure A9 about here.]

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[Figure A12 about here.]

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[Figure A14 about here.]

[Figure A15 about here.]

[Figure A16 about here.]

[Figure A17 about here.]

[Figure A18 about here.]

List of Figures

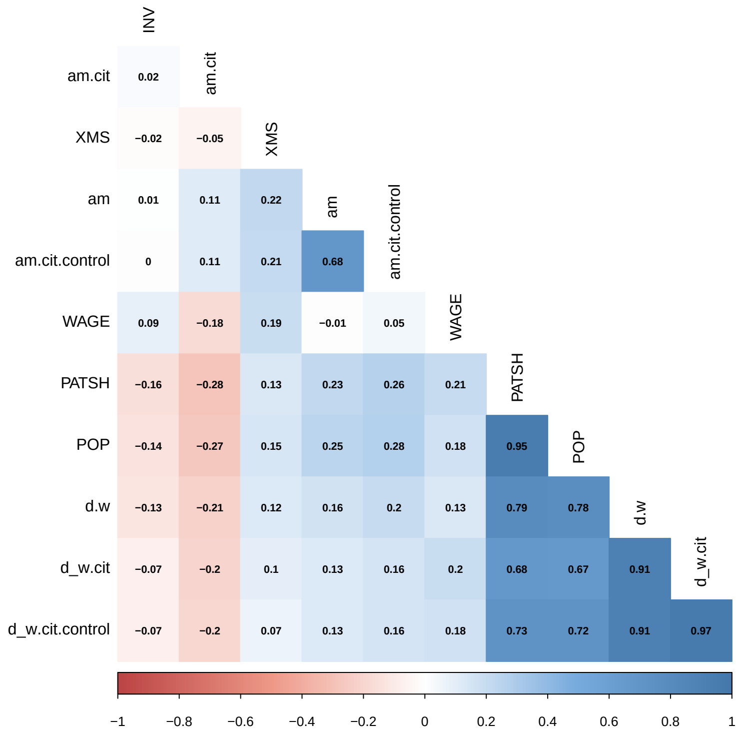
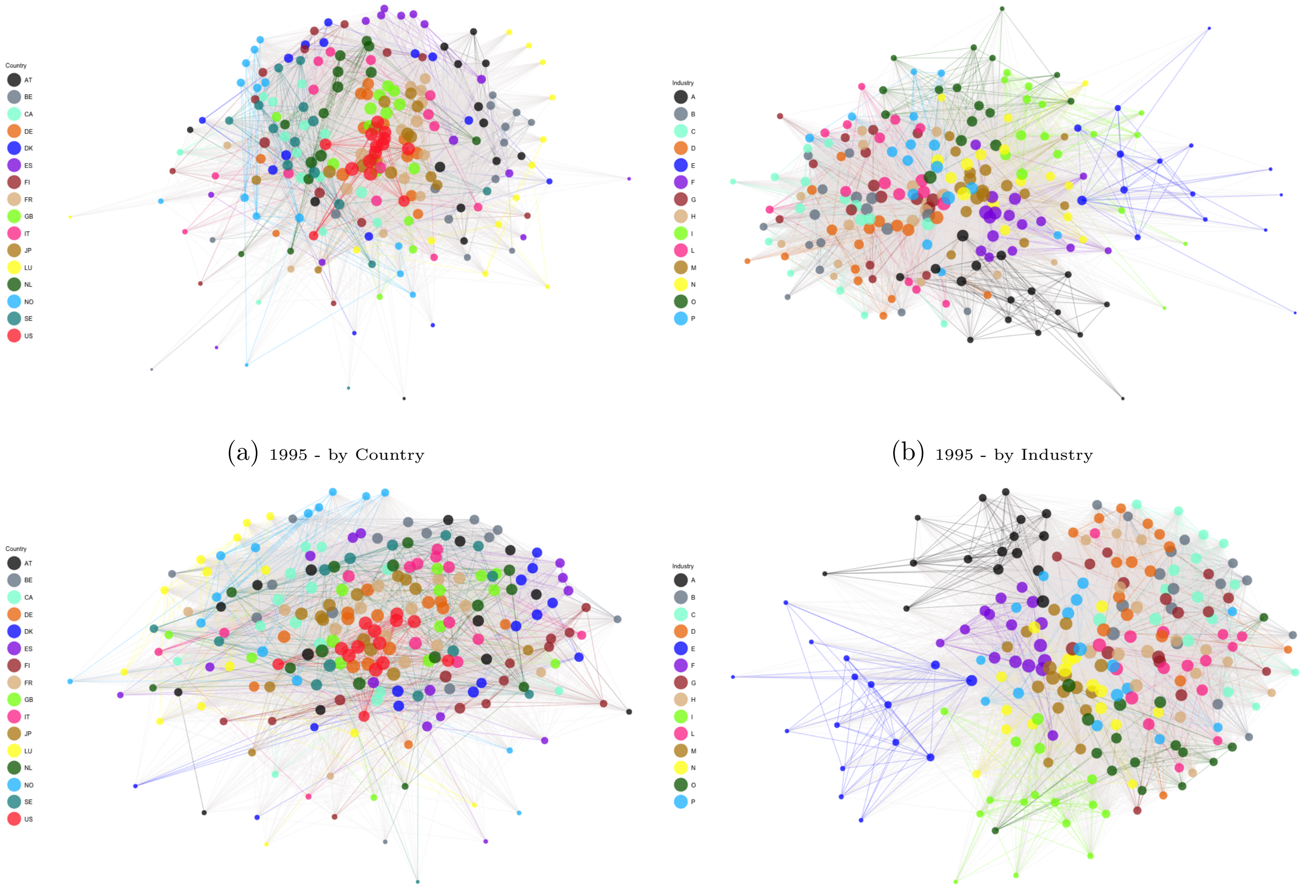


Figure A1: Correlation Matrix including Robustness Measures (.control)



(a) 1995 - by Country

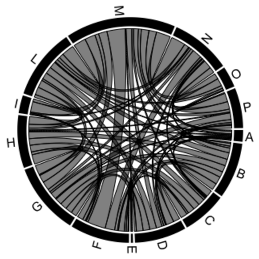
(b) 1995 - by Industry

(c) 2009 - By Country

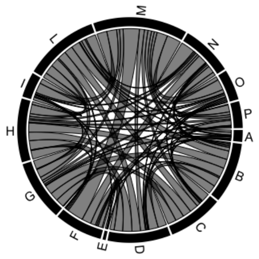
(d) 2009 - by Industry

In graphs (a) and (b) industry E for Luxembourg has been dropped for ease of visualization.

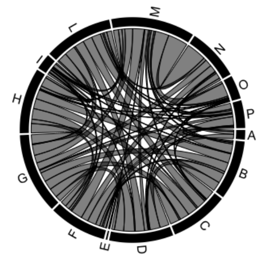
Figure A2: Citation Networks by Country and by Industry



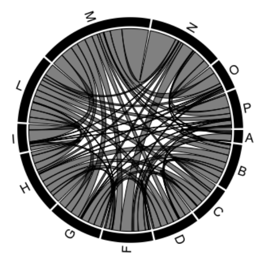
(a) 1995



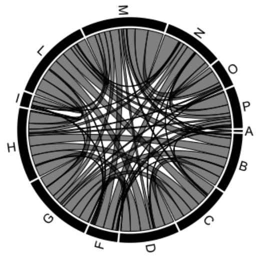
(b) 1996



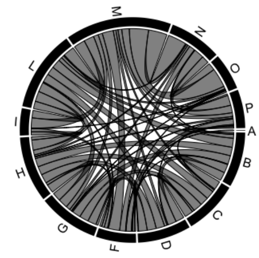
(c) 1997



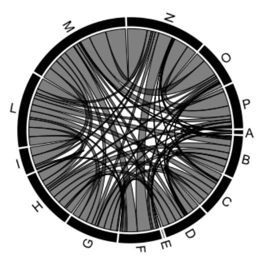
(d) 1998



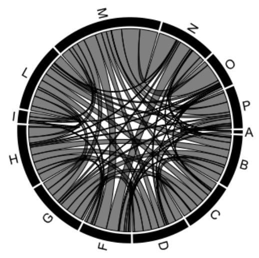
(e) 1999



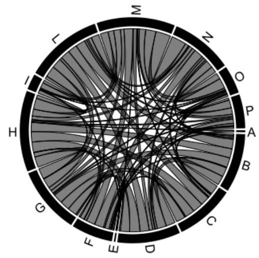
(f) 2000



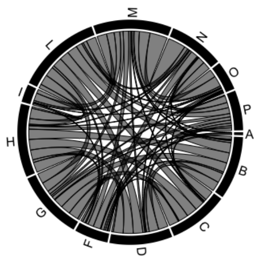
(g) 2001



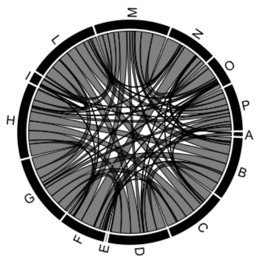
(h) 2002



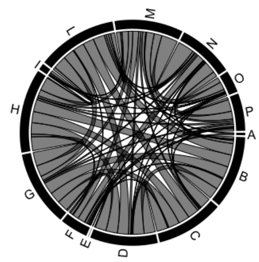
(i) 2003



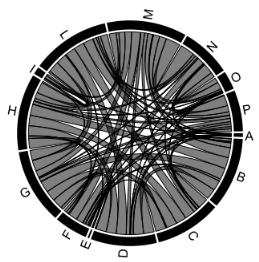
(j) 2004



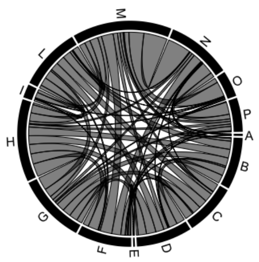
(k) 2005



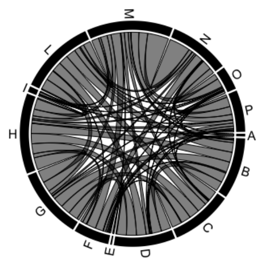
(l) 2006



(m) 2007



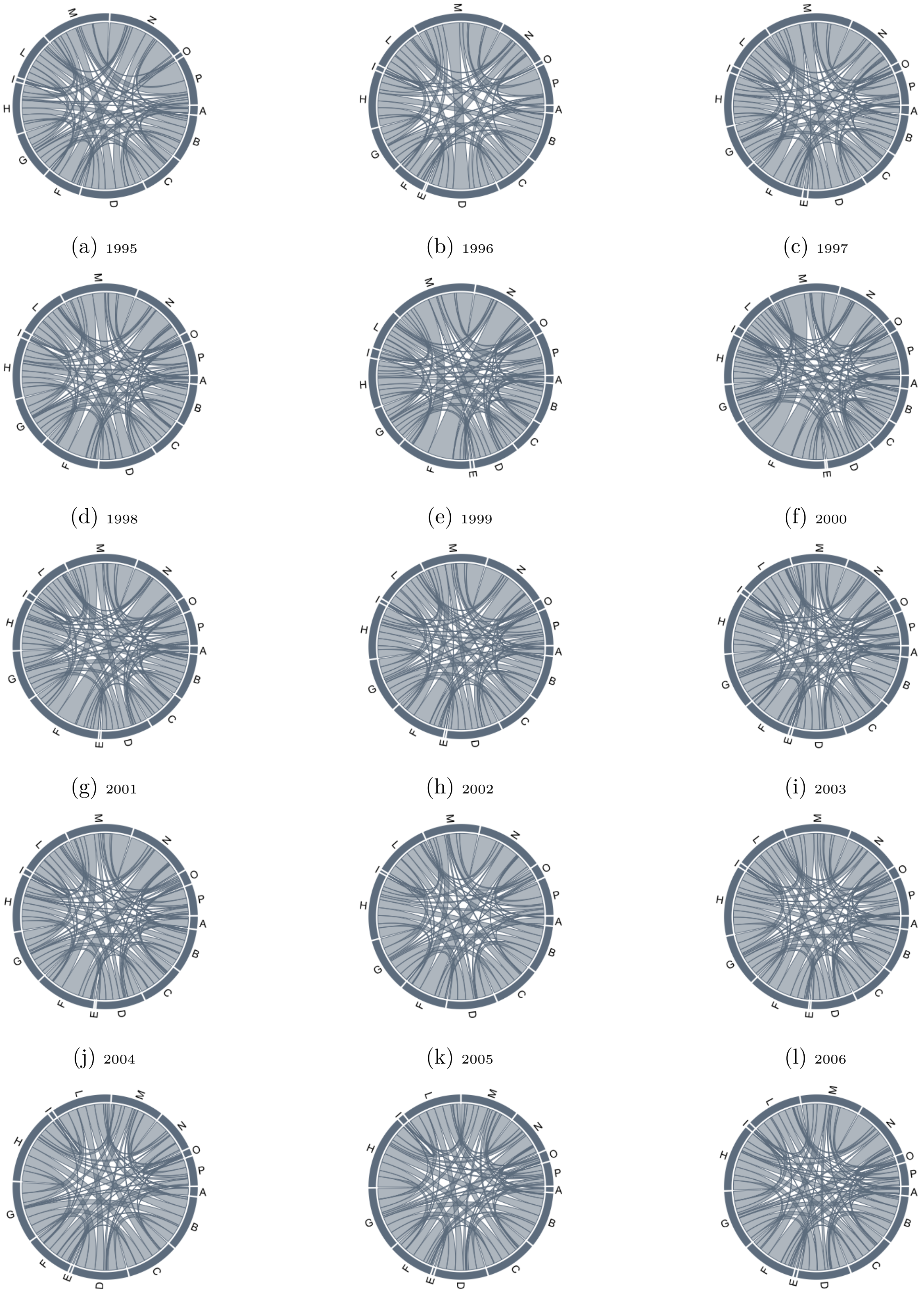
(n) 2008



(o) 2009

(Co-occurences)

Figure A3: Austria - Knowledge Space



(a) 1995 (b) 1996 (c) 1997

(d) 1998 (e) 1999 (f) 2000

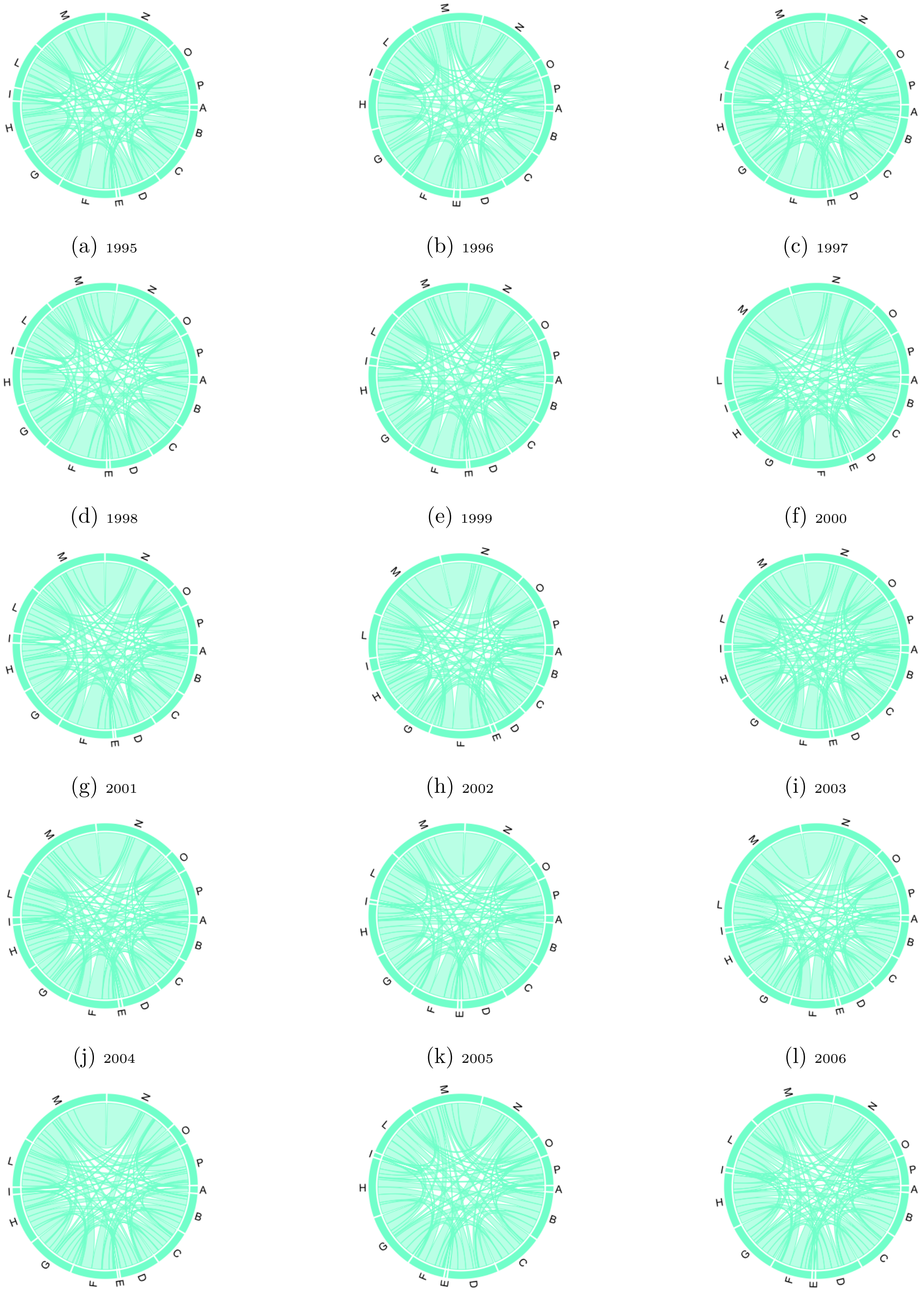
(g) 2001 (h) 2002 (i) 2003

(j) 2004 (k) 2005 (l) 2006

(m) 2007 (n) 2008 (o) 2009

(Co-occurences)

Figure A4: Belgium - Knowledge Space



(a) 1995 (b) 1996 (c) 1997

(d) 1998 (e) 1999 (f) 2000

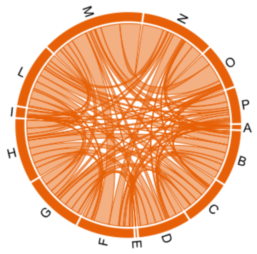
(g) 2001 (h) 2002 (i) 2003

(j) 2004 (k) 2005 (l) 2006

(m) 2007 (n) 2008 (o) 2009

(Co-occurences)

Figure A5: Canada - Knowledge Space



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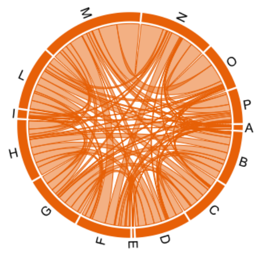
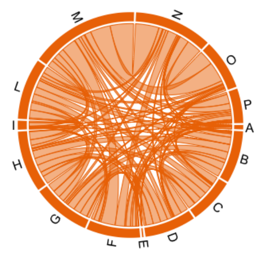
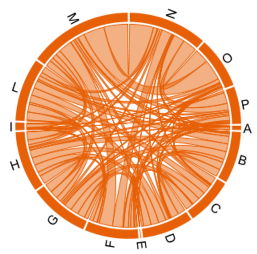


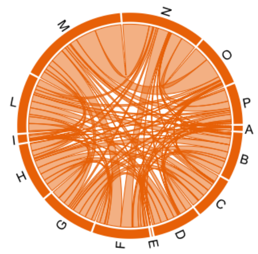
(b) 1996



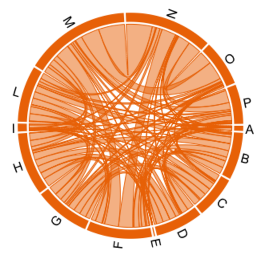
(c) 1997



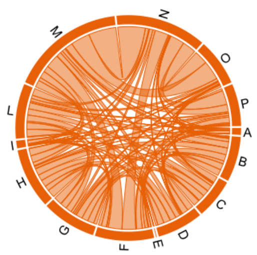
(d) 1998



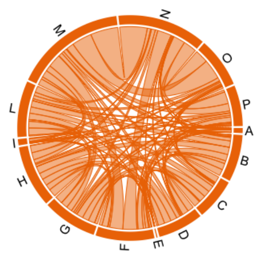
(e) 1999



(f) 2000



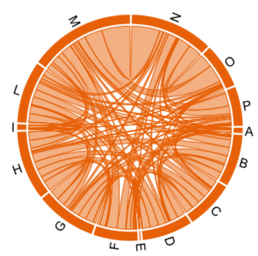
(g) 2001



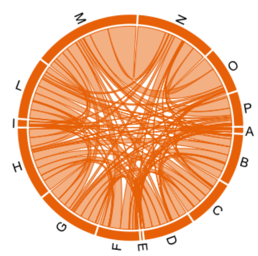
(h) 2002

(i) 2003

(j) 2004



(k) 2005



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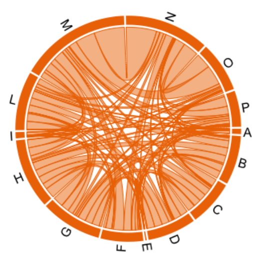

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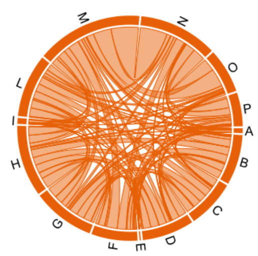

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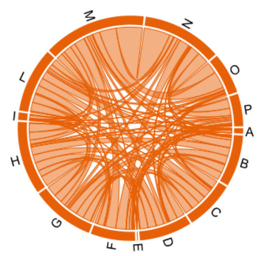
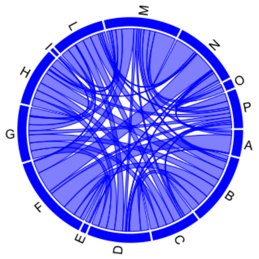


(o) 2009

(Co-occurences)

Figure A6: Germany - Knowledge Space



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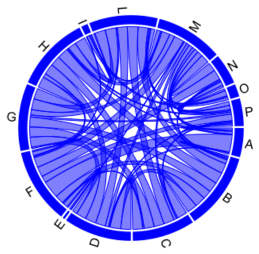
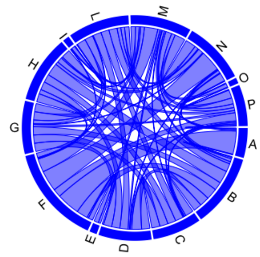
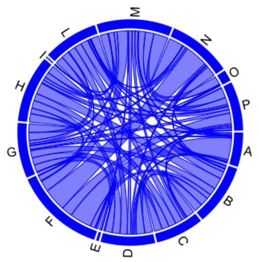


(b) 1996



(c) 1997



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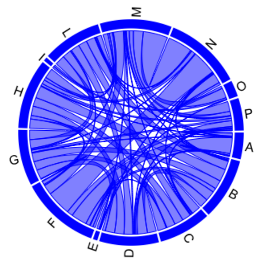

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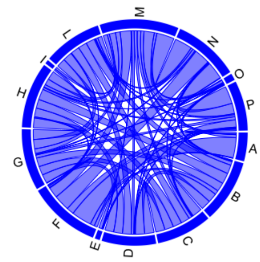
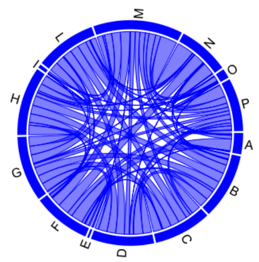
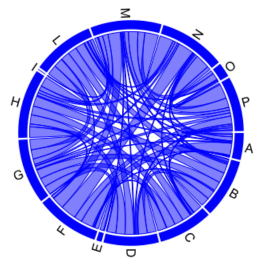


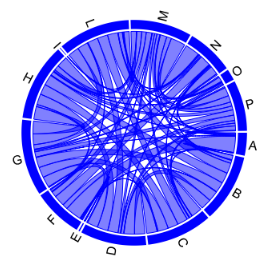
(f) 2000



(g) 2001



(h) 2002



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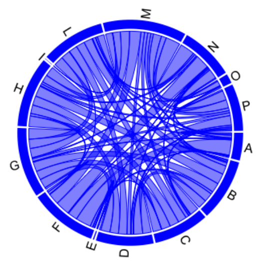

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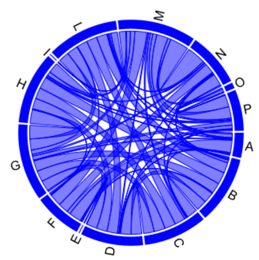

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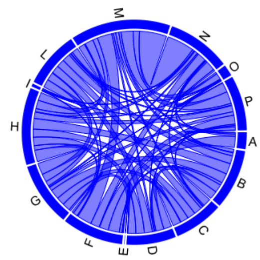

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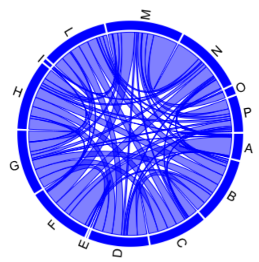

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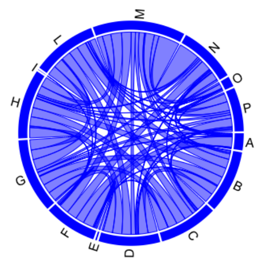
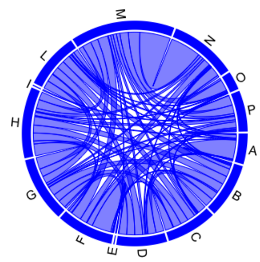


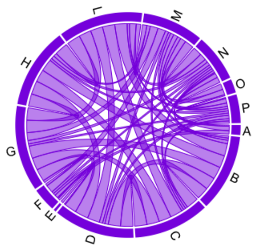
(n) 2008



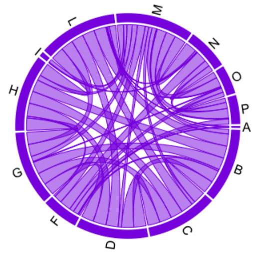
(o) 2009

(Co-occurences)

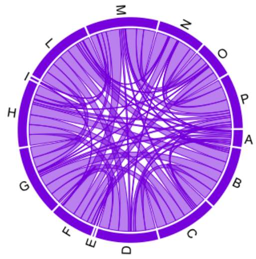
Figure A7: Denmark - Knowledge Space



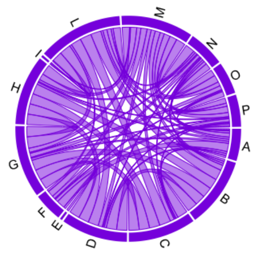
(a) 1995



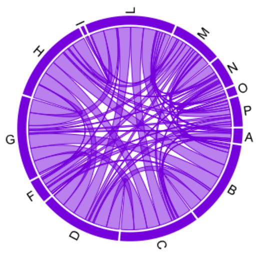
(b) 1996



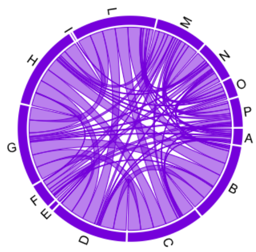
(c) 1997



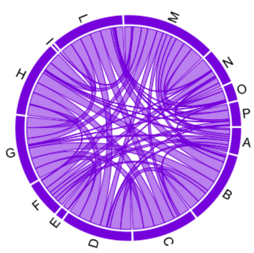
(d) 1998



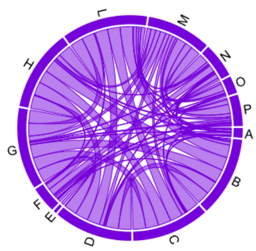
(e) 1999



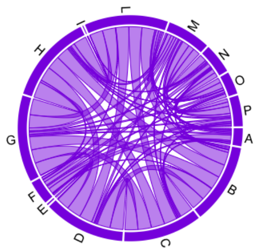
(f) 2000



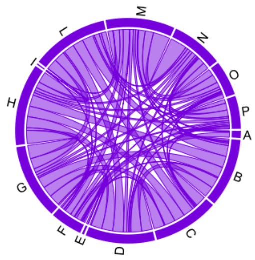
(g) 2001



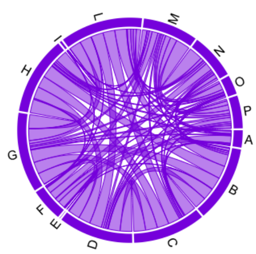
(h) 2002



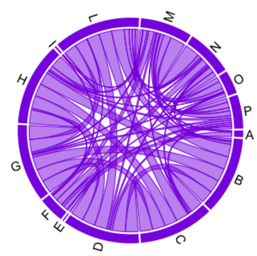
(i) 2003



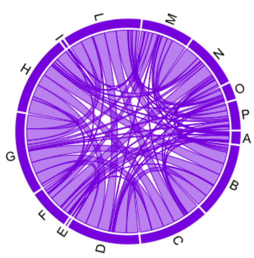
(j) 2004



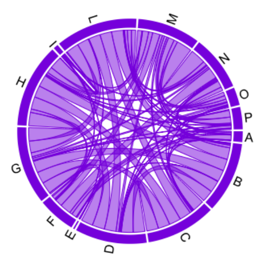
(k) 2005



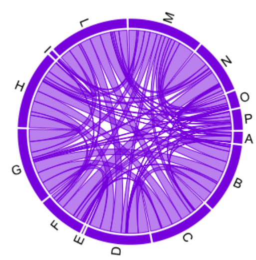
(l) 2006



(m) 2007



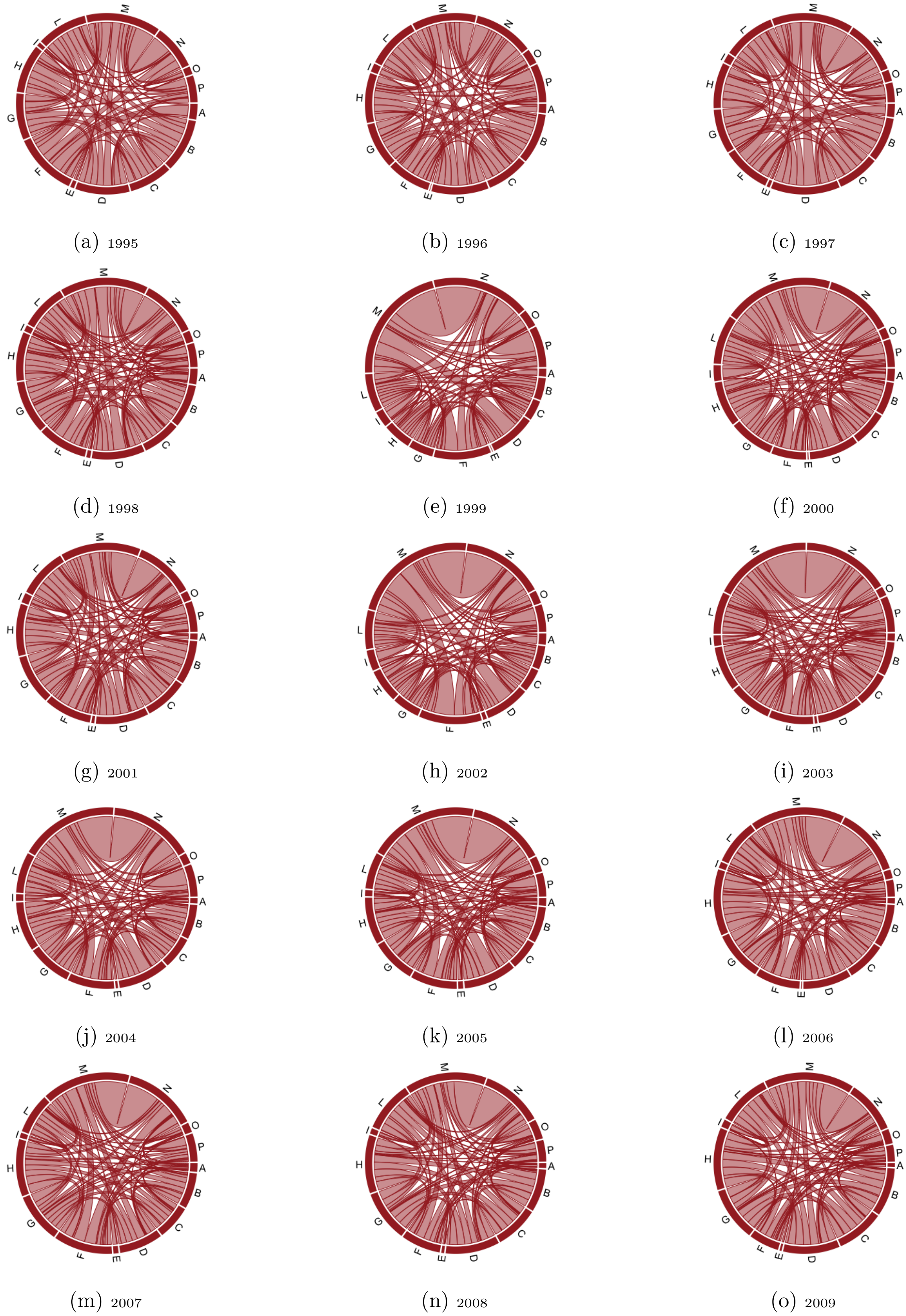
(n) 2008



(o) 2009

(Co-occurences)

Figure A8: Spain - Knowledge Space



(a) 1995 (b) 1996 (c) 1997

(d) 1998 (e) 1999 (f) 2000

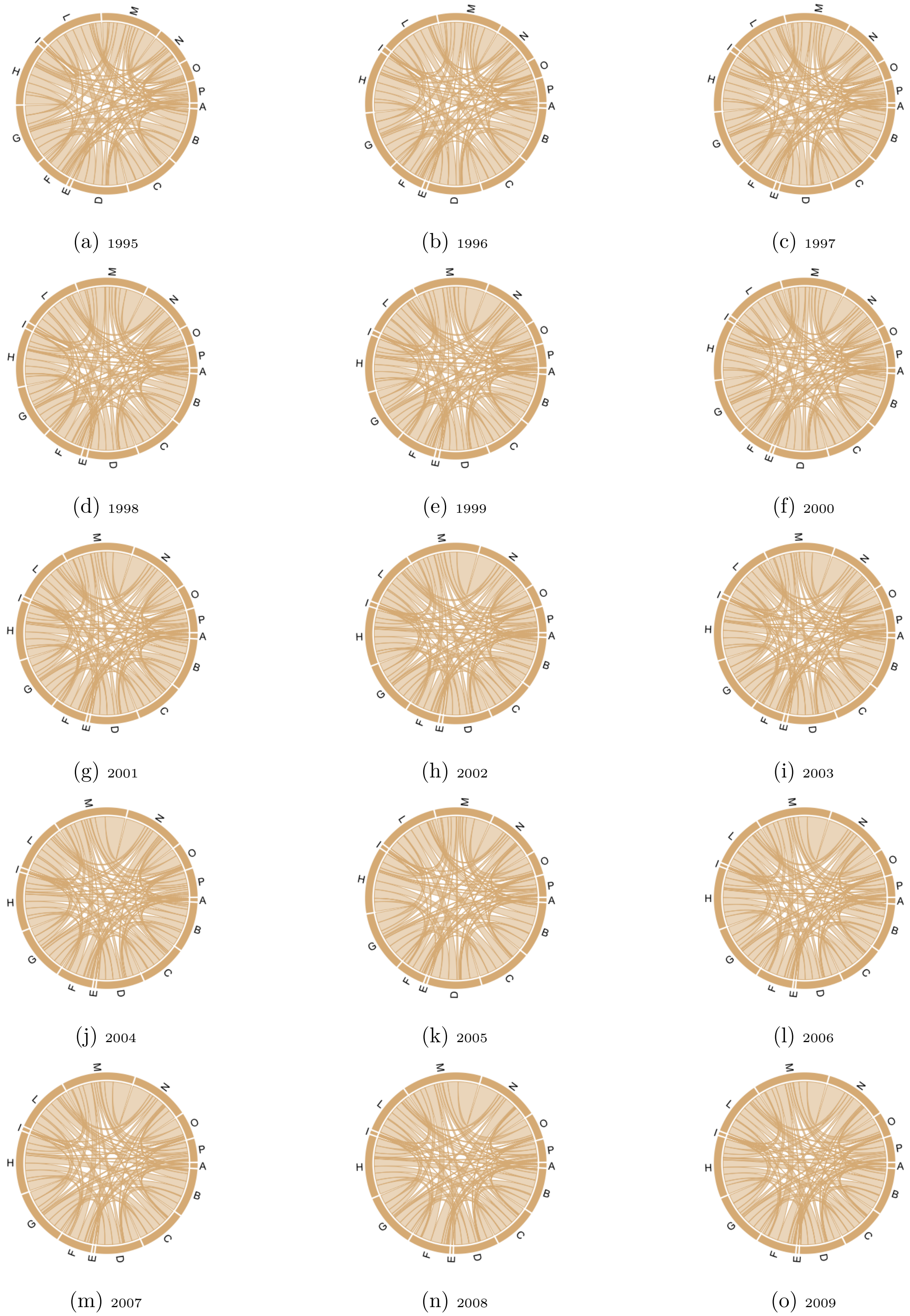
(g) 2001 (h) 2002 (i) 2003

(j) 2004 (k) 2005 (l) 2006

(m) 2007 (n) 2008 (o) 2009

(Co-occurences)

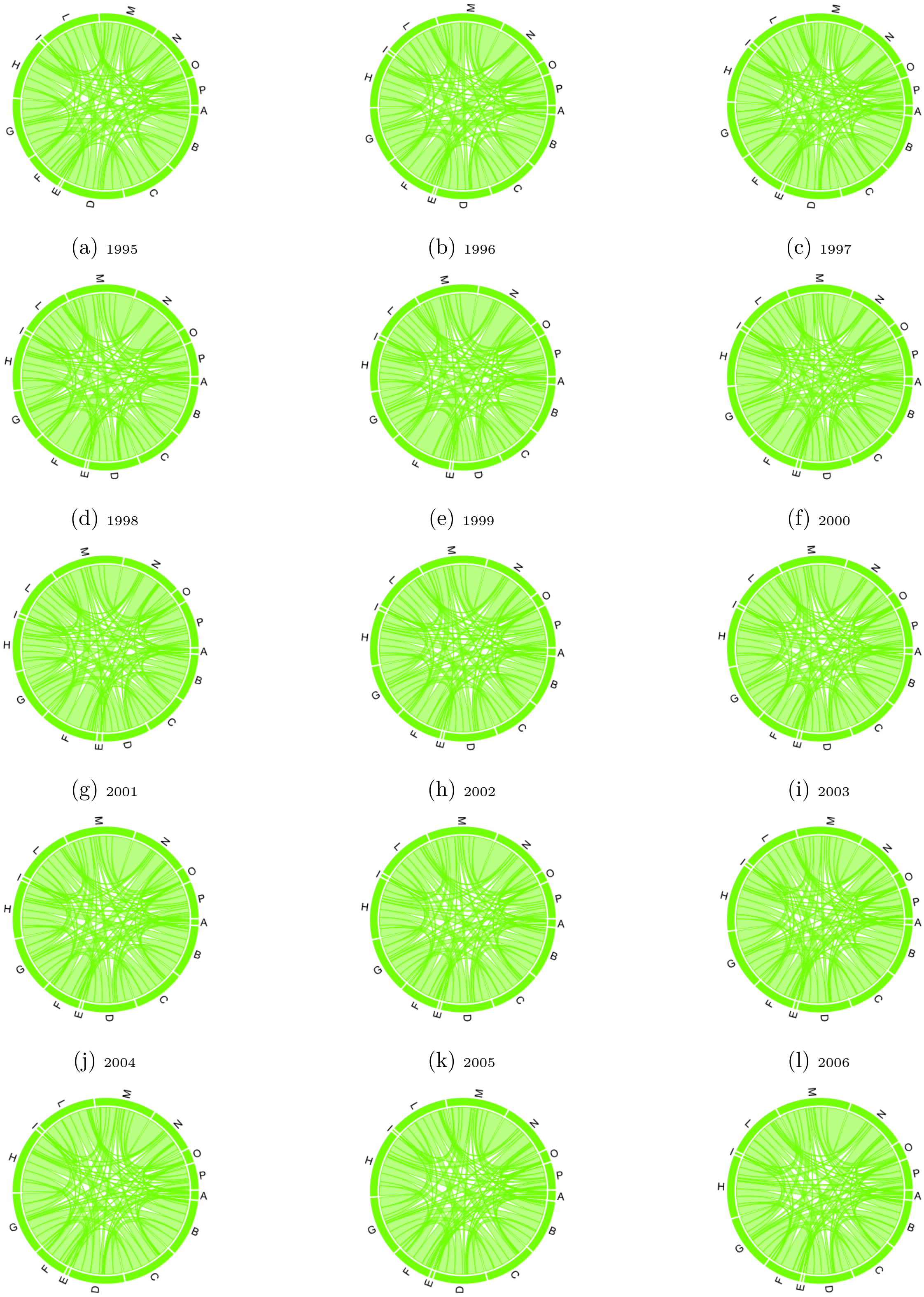
Figure A9: Finland - Knowledge Space



(a) 1995 (b) 1996 (c) 1997
(d) 1998 (e) 1999 (f) 2000
(g) 2001 (h) 2002 (i) 2003
(j) 2004 (k) 2005 (l) 2006
(m) 2007 (n) 2008 (o) 2009

(Co-occurences)

Figure A10: France - Knowledge Space



(a) 1995 (b) 1996 (c) 1997

(d) 1998 (e) 1999 (f) 2000

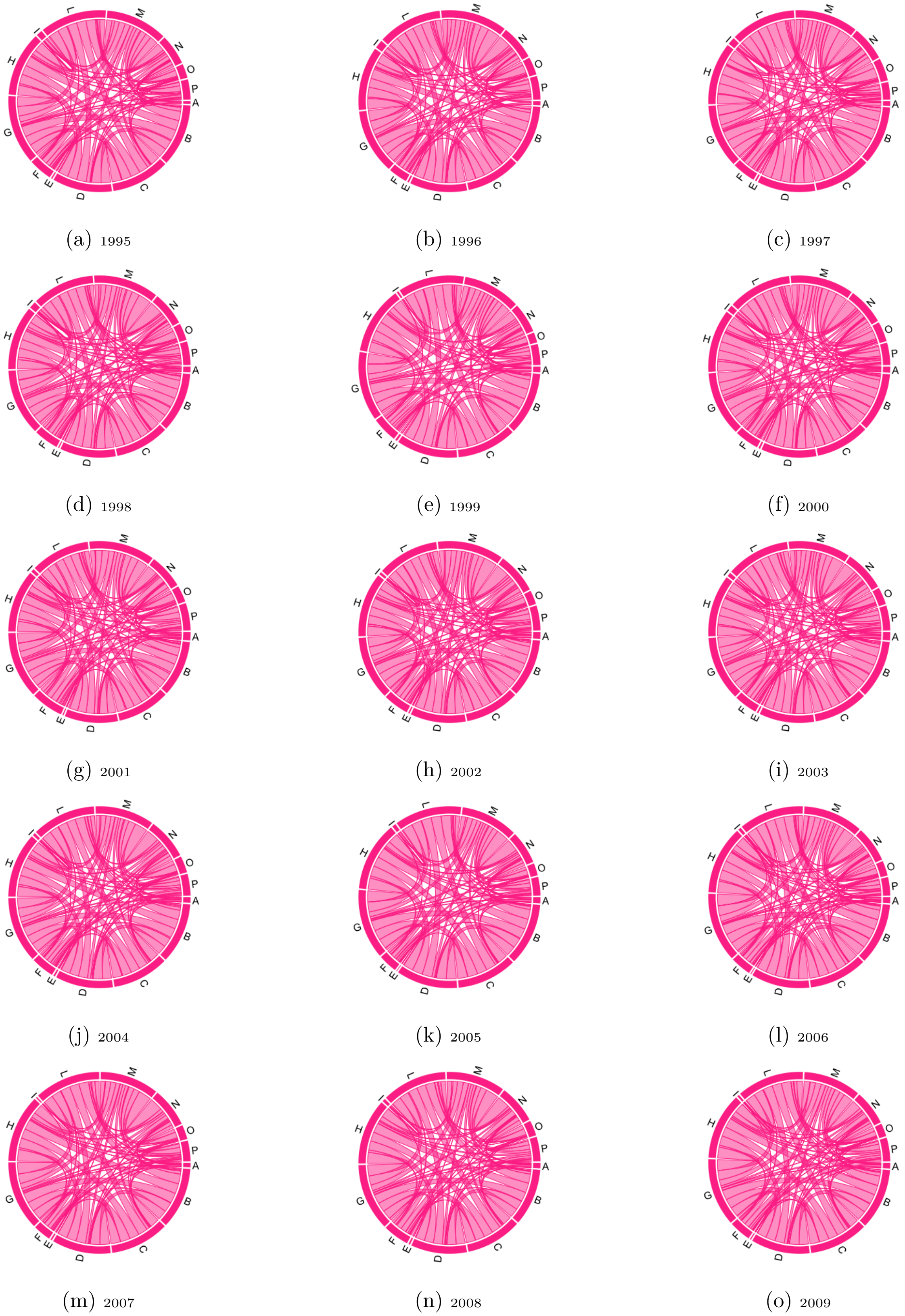
(g) 2001 (h) 2002 (i) 2003

(j) 2004 (k) 2005 (l) 2006

(m) 2007 (n) 2008 (o) 2009

(Co-occurences)

Figure A11: United Kingdom - Knowledge Space



(a) 1995 (b) 1996 (c) 1997

(d) 1998 (e) 1999 (f) 2000

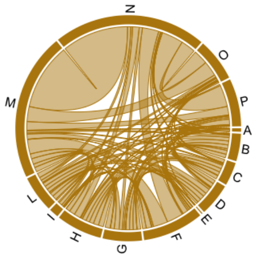
(g) 2001 (h) 2002 (i) 2003

(j) 2004 (k) 2005 (l) 2006

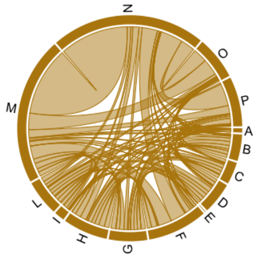
(m) 2007 (n) 2008 (o) 2009

(Co-occurences)

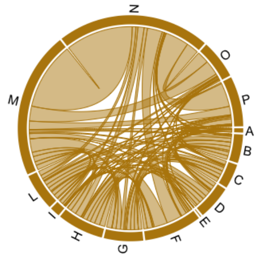
Figure A12: Italy - Knowledge Space



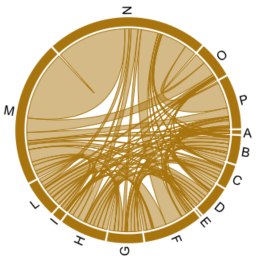
(a) 1995



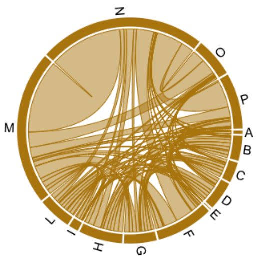
(b) 1996



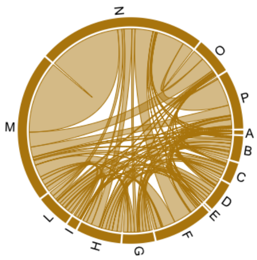
(c) 1997



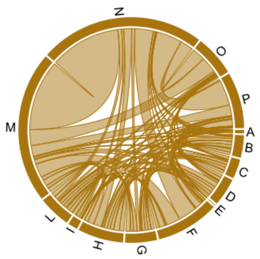
(d) 1998



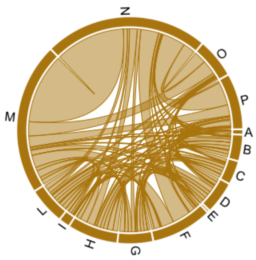
(e) 1999



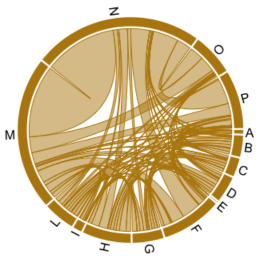
(f) 2000



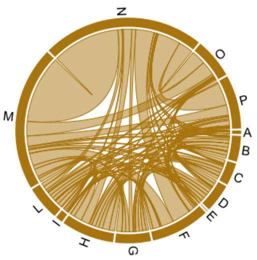
(g) 2001



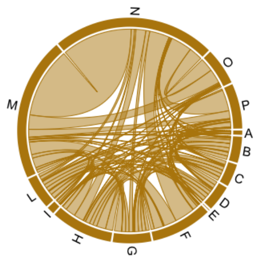
(h) 2002



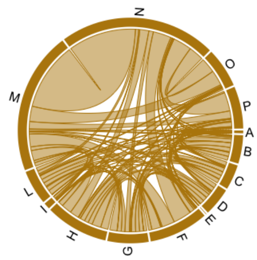
(i) 2003



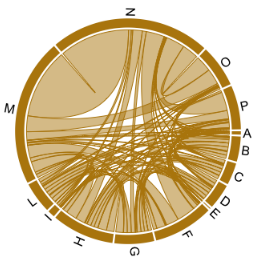
(j) 2004



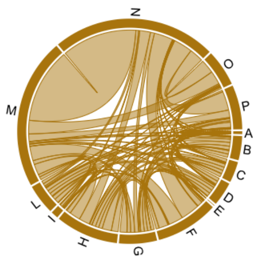
(k) 2005



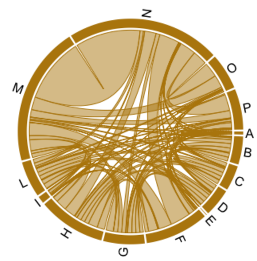
(l) 2006



(m) 2007



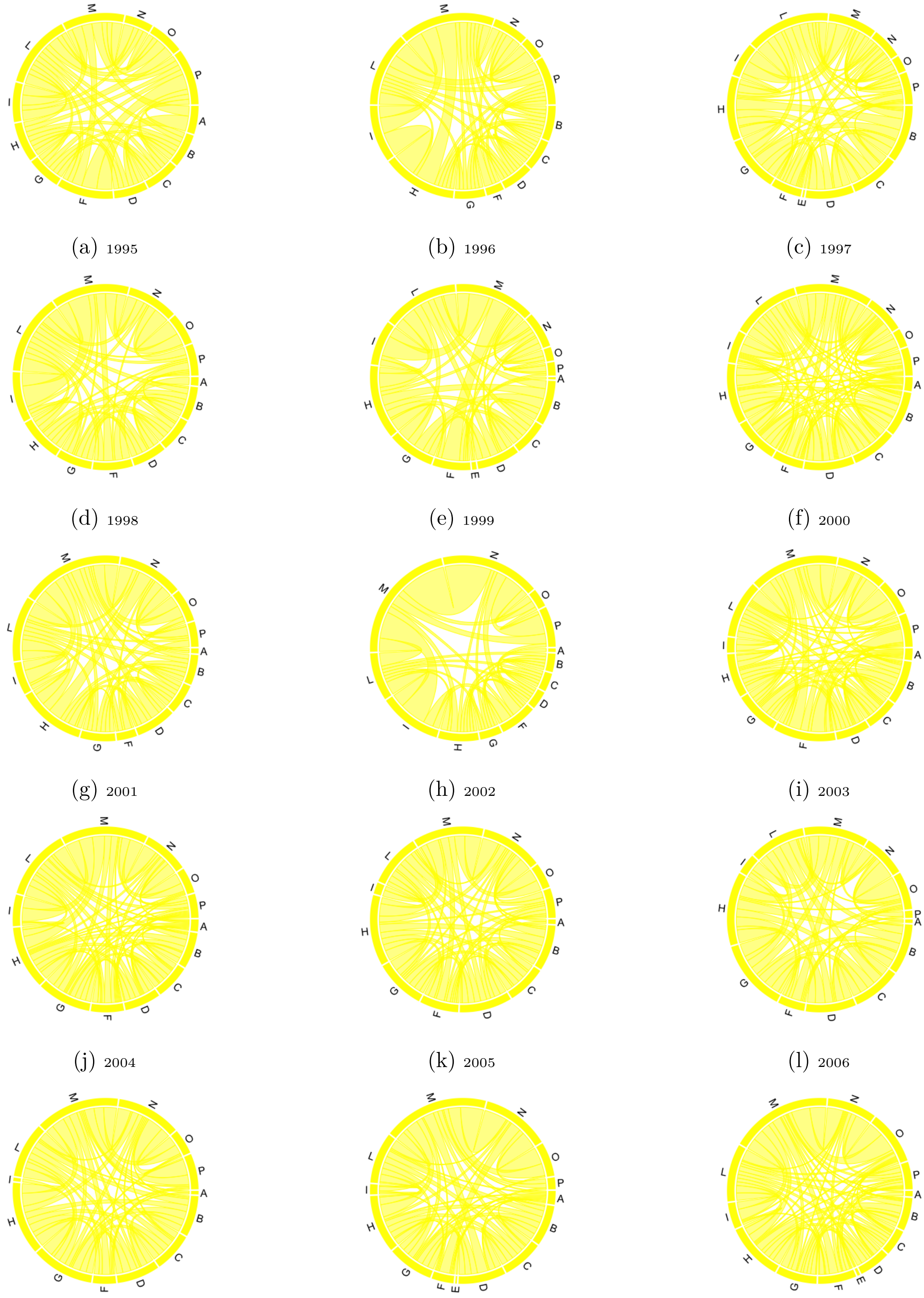
(n) 2008



(o) 2009

(Co-occurences)

Figure A13: Japan - Knowledge Space



(a) 1995 (b) 1996 (c) 1997

(d) 1998 (e) 1999 (f) 2000

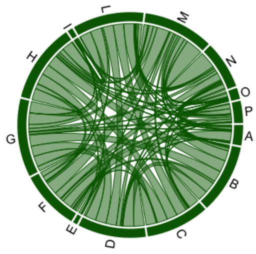
(g) 2001 (h) 2002 (i) 2003

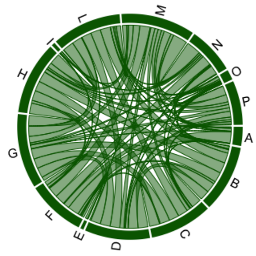
(j) 2004 (k) 2005 (l) 2006

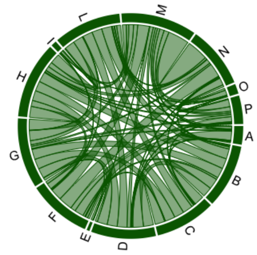
(m) 2007 (n) 2008 (o) 2009

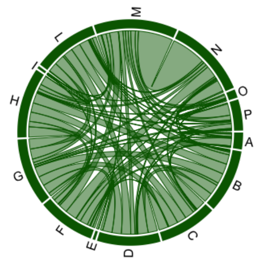
(Co-occurences)

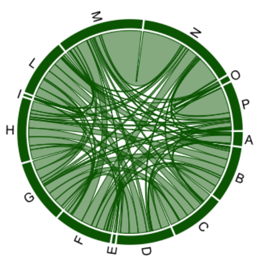
Figure A14: Luxembourg - Knowledge Space

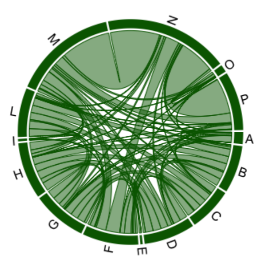

(a) 1995

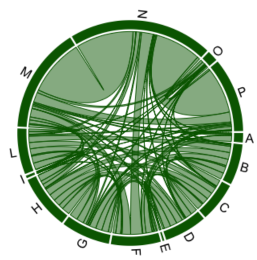

(b) 1996

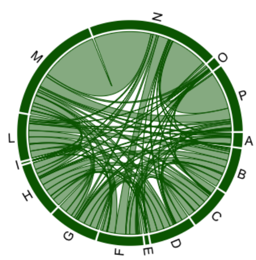

(c) 1997

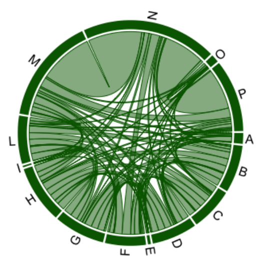

(d) 1998

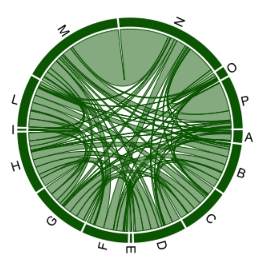

(e) 1999

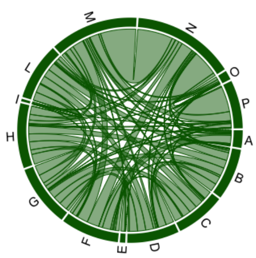

(f) 2000

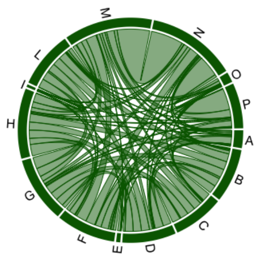

(g) 2001

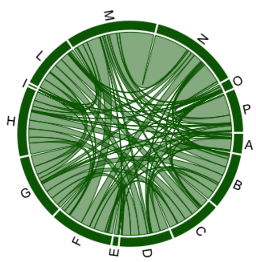

(h) 2002

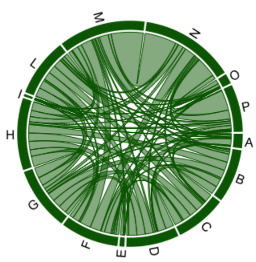

(i) 2003

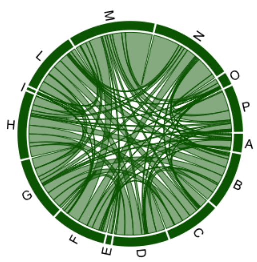

(j) 2004


(k) 2005


(l) 2006

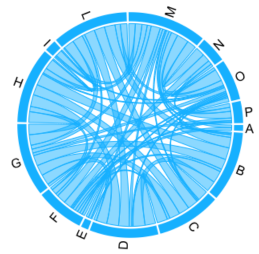

(m) 2007

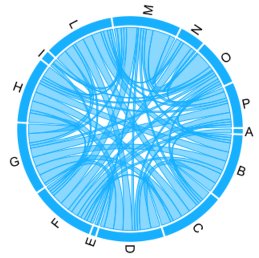

(n) 2008

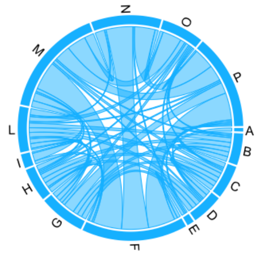

(o) 2009

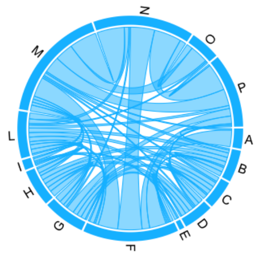
(Co-occurences)

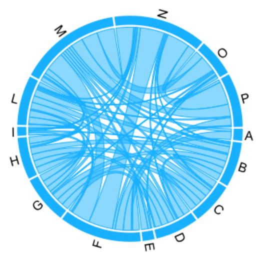
Figure A15: Netherlands - Knowledge Space

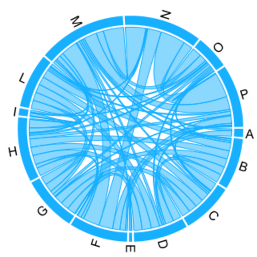

(a) 1995

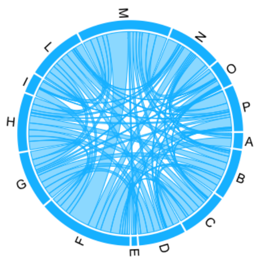

(b) 1996

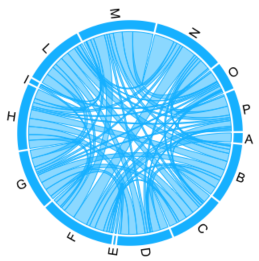

(c) 1997

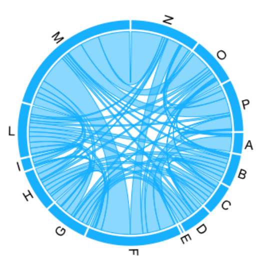

(d) 1998

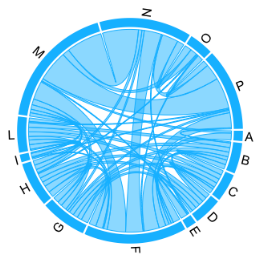

(e) 1999

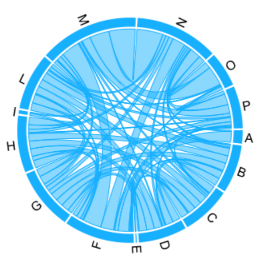

(f) 2000

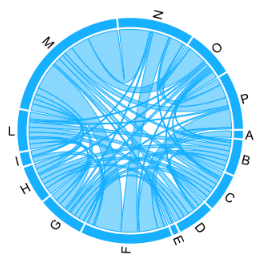

(g) 2001

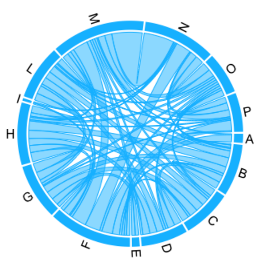

(h) 2002

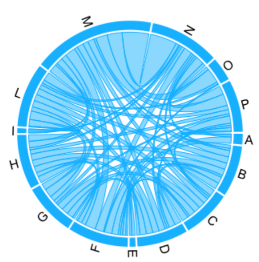

(i) 2003

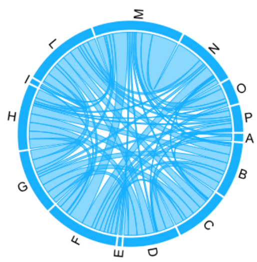

(j) 2004


(k) 2005


(l) 2006

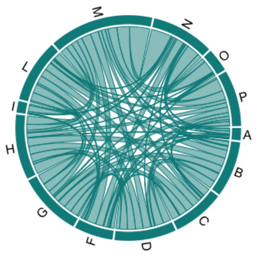

(m) 2007


(n) 2008

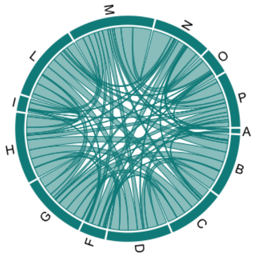

(o) 2009

(Co-occurences)

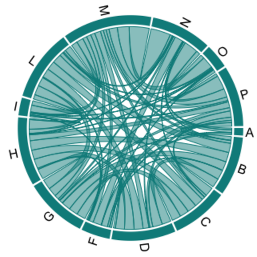
Figure A16: Norway - Knowledge Space



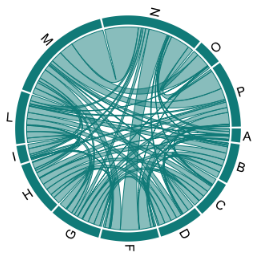
(a) 1995



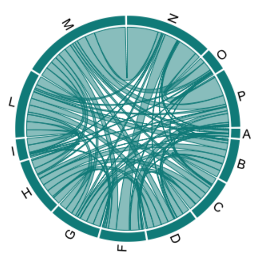
(b) 1996



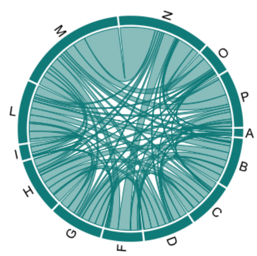
(c) 1997



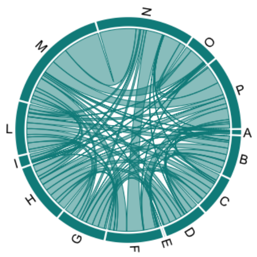
(d) 1998



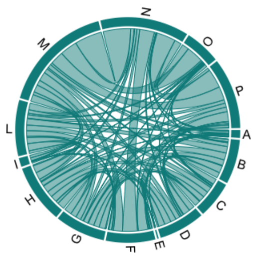
(e) 1999



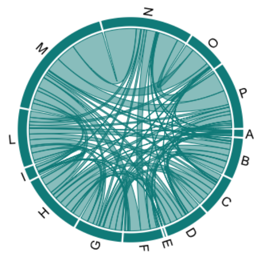
(f) 2000



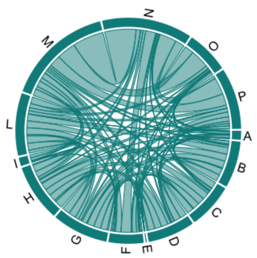
(g) 2001



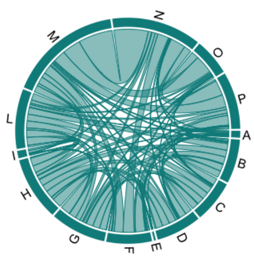
(h) 2002



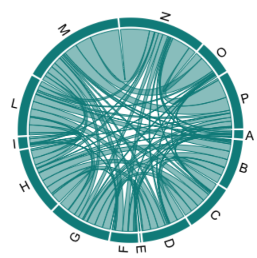
(i) 2003



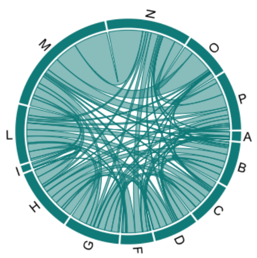
(j) 2004



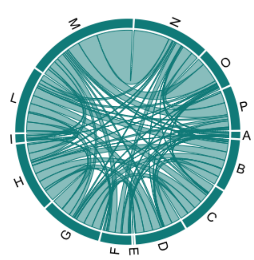
(k) 2005



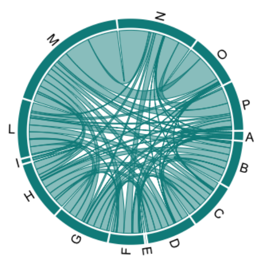
(l) 2006



(m) 2007



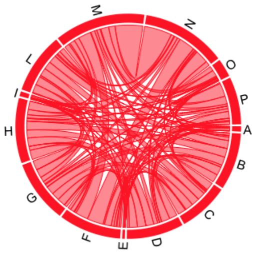
(n) 2008



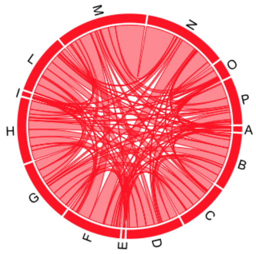
(o) 2009

(Co-occurences)

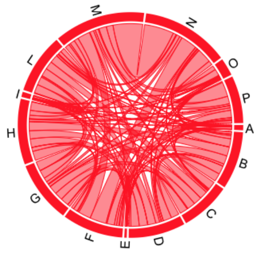
Figure A17: Sweden - Knowledge Space



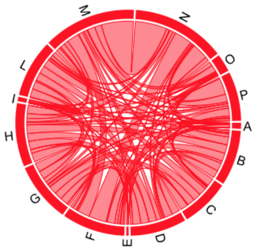
(a) 1995



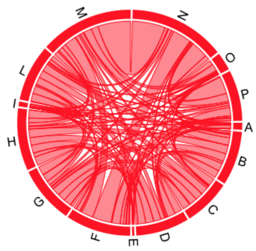
(b) 1996



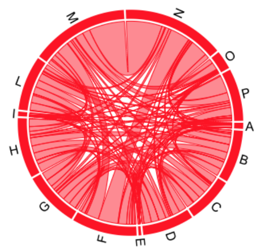
(c) 1997



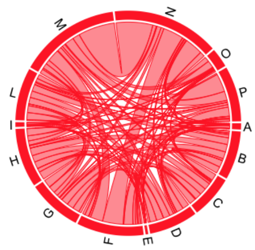
(d) 1998



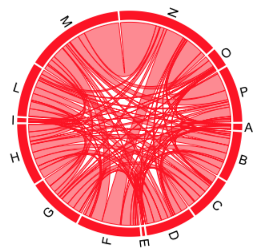
(e) 1999



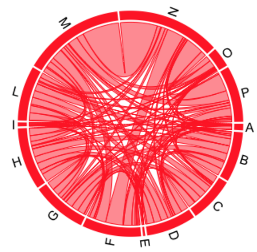
(f) 2000



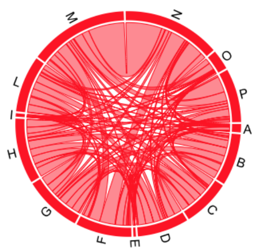
(g) 2001



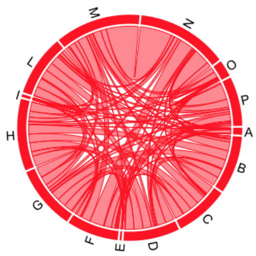
(h) 2002



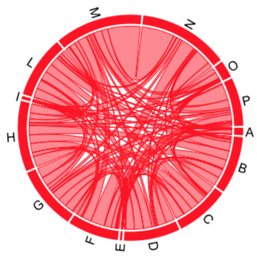
(i) 2003



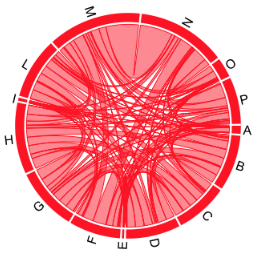
(j) 2004



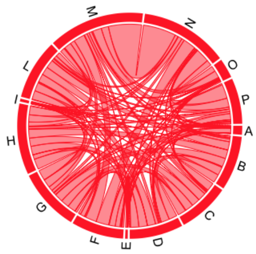
(k) 2005



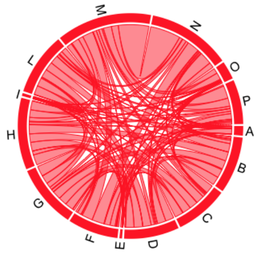
(l) 2006



(m) 2007



(n) 2008



(o) 2009

(Co-occurences)

Figure A18: United States - Knowledge Space