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Bridging Technologies in the Regional Knowledge Space: Measurement and Evolution

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Abstract

The concept of Bridging Technologies (BTs) refers to technologies which are important for the regional knowledge base by connecting different fields and thereby enabling technological development. We provide analytical tools to identify BTs and study their evolution over time. We apply these tools on several levels. Our findings indicate that large patenting regions are not necessarily the ones that embed most new technologies in their Knowledge Space (KS). Our findings reveal that the German KS became less dependent on important technologies, such as transport, machinery and chemicals over the period 1995-2015. Changes in the German KS in terms of the development of new BTs are due to a regionally dispersed process rather than driven by single regions.

Keywords: Knowledge Spaces; Network Analysis; Bridging Technology; Revealed Relatedness; GPT; Centrality

JEL Classification: O33; O34; R11

1 Introduction

Technological change is an evolutionary process, it is cumulative in the sense that it is building on previous technical findings in combination with new elements. These elements are more fertile when they are combined with other technologies or allow to connect previously disconnected technological fields (Pavitt, 1984; Jaffe, 1989).

General Purpose Technologies (GPTs) and Key Enabling Technologies (KETs) are such particularly fertile technologies which have been identified as sources of economic growth and technical progress. Complementary sectors benefit in terms of productivity and technical improvement from innovations in GPTs. The steam engine, electric motors and semiconductors are examples for such technologies that have driven industrial development in the past (Bresnahan & Trajtenberg, 1995). KETs are defined as technologies that permit the development of sub-technologies which cannot exist without the main KET. An example would be Information and Communication Technologies (ICT) that permitted industrial automation in manufacturing (Posada et al., 2015).

Technologies can be thought of as structural elements within the Knowledge Space (KS) with particular functions and properties. The KS is represented by the network of relations between different technologies and its structure is considered important for the accumulation and production of knowledge (Kogler et al., 2013). The KS is not static but changes over time and is, among others, affected by the emergence of General Purpose Technologies (GPTs) and Key Enabling Technologies (KETs). A possible expectation is that a key technology will hold a central position in the KS. This can affect the improvement (new inventions) of the other technologies connected to this main node (Graf, 2012).

We define a Bridging Technology based on its function to serve as a connecting element between many other technologies in the KS, thereby assuming a central position in the KS. A common feature of BTs, similar to KETs and GPTs, is that developments in a BT have the potential to affect innovation in many other areas. The main difference is that in contrast to GPTs and KETs, BTs are not defined ex ante and are not necessarily global, but are identified within each KS based on its position and functionality. We propose two different definitions of BTs and develop two different indicators for identifying them.

The indicators are inspired by Social Network Analysis (SNA) methods applied on the KS. In particular, we develop a measure called Bridging Index (BI) that accounts for degree centrality (to understand how strongly related a technology is with others) combined with a diversification index (to assess the distribution of these connections). As an alternative to this index, we capture the idea of bridging in a network with Betweenness Centrality (BC). The index captures the number of times a node is on the shortest path between all other nodes, to explain which technologies are responsible for the diffusion of knowledge in the KS.

We use the PATSTAT database, Autumn 2017 and technologies are defined based on the Cooperative Patent Classification (CPC) on the 4-digit level. The analysis is performed for the region of Jena located in the former GDR. We choose Jena as a case study region since it is a strong patenting region and its innovation system has been analysed in several studies (Graf, 2006; Fritsch & Graf, 2010; Graf & Broekel, 2020) so that we can validate our results when applying the bridging indices. We use both co-occurrence and Revealed Relatedness matrices of CPC classes to reconstruct the KS. The period of analysis is from 1990 (after German reunification) until 2015 with 5-year moving windows, to identify the BTs, track their development, and their change in position in the KS.

We apply both indicators by looking at the development of technologies over time, to identify changes in the main BTs in Jena. To be able to compare results across regions, we propose the Revealed Bridging Advantage (RBA), a specialization index inspired by the Balassa indicator. We group CPC classes into technological fields based on Schmoch (2008) for Jena and then compare the results with Germany to observe differences in terms of bridging technologies between Jena and Germany. Thereby we contribute to the scarce literature on BTs and to the general understanding on how these are formed in knowledge spaces.

We proceed as follows. In the next section, we review the literature on structural change, innovation, GPTs, KETs, and KS as a background for the discussion of the properties of bridging technologies. In section 3, we provide two alternative definitions of bridging technologies. In section 4, we develop the methodologies used to reconstruct the KS of Jena and present the analytic tools for measuring bridging technologies according to the two definitions. In section 5, we present results on the technological development of Jena's KS. In section 6, we develop and apply the RBA index for cross-regional comparisons of BTs. Finally, we conclude with a general overview of our findings and suggestions for applications and further analysis.

2 Literature Review

2.1 Structural Change and Innovation

Many studies distinguish between different types of technologies based on their potential impact on growth. A fundamental distinction is between radical and incremental technological innovations. Firms often lack the knowledge and requirements to support radical innovations, because they introduce a high degree of novelty. Radical innovations render existing competences obsolete and redefine the concept of competitive advantage, sometimes by creating completely new industries. This concept is in line with the view of Schumpeter's "creative destruction". Incremental innovations on the other hand do not reshape economies but rather ameliorate what is already existing, solving problems on the production or distribution flow (Schumpeter, 1934; Dosi, 1982; Abernathy & Clark, 1985; Scott, 2006).

Already Schumpeter (1939) in his work on technical innovation and growth identified different cycles of economic development initiated by prominent technologies. The first wave of economic and technological change was taken up by the steam engine and the textile industry in the 18th century, the second by railways and subsequent improvements in the steel industry and the last one by electric power, chemistry and the combustion engine. Some of these (such as the steam engine and electricity) were identified as GPTs in the subsequent evolutionary economics literature.

In his seminal contribution, Dosi (1982) used the concept of technological paradigms to discuss the role of continuous changes and discontinuity for innovation. In this paper, factors important for the emergence of a new paradigm were identified: scientific advances, economic factors, institutional variables and difficulties along previous technological paths. All of them can contribute to the selection of a new paradigm and so to a new development path. Technologies actually evolve and after some time (after the maturity phase) are substituted by a new paradigm, that drives another phase of economic and technological development.

In a subsequent article, Dosi (1988) identified important aspects influencing technological progress. Technological advancements are achieved thanks to exploitation of both public (something known by all the actors involved in the process) and private knowledge (that is not publicly available: patents, tacit knowledge etc.). He defined *untraded interdependencies* as competences shared between different sectors that can be seen as *collective assets* of multiple firms established within a region or country. These capabilities have the ability to pass from one sector to another and they are: *country specific*, *region specific* or even *company specific*. These are fundamental for innovative activities and they are defining the possible incentives or limitations of innovation. Knowledge can pass from one industry to another one and it is embedded in some geographical boundaries (nationwide or region-wide).

Dosi & Nelson (1994) argue that firms are the most important actors in the process of technological improvement, they are the ones that invest in the new prominent technologies and develop tangible goods for the society. They are the driver of technological progress and change.

The new technology increases the profit of firms with a subsequent investment boom and increase of wages. It is important to understand not only the possible technical enhancements introduced by a new technology (doing things faster and better) but also the actual economic effects on the whole society. The literature is rich of case studies on how new technologies change and reshape the economy (with pioneering firms reaping higher profits than the rest) (Tushman & Anderson, 1986; Bresnahan, 1986).

Another strand of literature shifted the focus towards economic geography, trying to apply the main concepts and definitions from evolutionary economics (such as *selection*, *path-dependency*, *chance* and *increasing returns*) to geography. The main intention was to understand how the spatial environment reacts to changes in the technological sphere. Evolutionary theories provide possible explanations for phenomena on the geographical level, such as collective learning processes, regional problems with increasing worldwide product variation and the spatial formation of new industries (Boschma & Lambooy, 1999).

2.2 General Purpose Technologies and Key Enabling Technologies

The general idea of GPTs originated in some of the studies cited above (Tushman & Anderson, 1986; Bresnahan, 1986). Trajtenberg (1990) study how CT scanners were a source of product innovation and how it managed to combine different existing technologies in the market. Bresnahan (1986) investigate how computers affected financial services. Both studies stated that computerization had, already, a huge impact on other sectors, namely: health care and large organizations. This strand of literature also points out how different technologies can be complementary to each other (Bresnahan, 2010).

All this contributed to a more precise definition of GPTs and their characteristics. In their seminal study, Bresnahan & Trajtenberg (1995) explicitly define and discuss the features of a GPT referring to the examples of the steam engine, electric motors, semiconductors and computers. Progress and growth in a region, nation or worldwide is driven by some technologies. Advancement and innovation are not made in isolation but in combination with other sectors that can benefit from the improvements in the “main technology”. Rosenberg & Trajtenberg (2004) retrieve the features of GPTs by taking the example of the steam engine. First, GPTs have *general applicability* that is defined as a generic feature that permits the GPT to be fundamental for a large number of applications and processes. Secondly, they manifest *dynamism* which means that they experience continuous innovation, defined as improvements of the existing technology using new configuration systems (Boer & Gertsen, 2003), that increase efficiency for users and help diffusion in other sectors. In the literature, this connected characteristic is called *pervasiveness* and it is usually used in combination with technological diversification (Malerba & Orsenigo, 1997; Cantner & Vannuccini, 2017). Fourth, they have *innovational complementarities* in the sense that when a GPT is improved it also creates incentives to ameliorate the connected technologies (Rosenberg & Trajtenberg, 2004). All these characteristics create loops in which the better performances of an industry or technology connected to the GPT creates incentives also to invest in the GPT itself. This creates a particular environment in which the GPT as well as a connected industry can profit from the highest reached performance of either of the two (Cantner & Vannuccini, 2017). In our case, we are mostly interested in the *pervasiveness* and *innovational complementarities*; the former creates new combinations between GPTs and previously unrelated technological fields while the latter induce the innovative activities of the connected technologies in the KS. This happens when the costs to generate further advances in the mainstream technology are too high, so that new opportunities to connect previously unrelated fields become economically attractive (Malerba & Orsenigo, 1997; Graf, 2012).

The definition provided by Bresnahan & Trajtenberg (1995) and the contemporary research on the characteristics of GPTs opened possibilities to actually study the diffusion and growth of these technologies. Helpman & Trajtenberg (1994) develop a growth model in which new GPTs substitute old ones and thereby start a new development cycle characterized by a new paradigm with new connections to complementary inputs. In a subsequent study, Helpman & Trajtenberg (1996) analyze the diffusion of GPTs in final goods sectors. They assume that the adoption phase is gradual across sectors and show that only after a critical mass of sectors adopted the new technology it pays for companies to make new investments in R&D and thereby spur sustained growth.

Hall & Trajtenberg (2004) relate the emergence of GPTs with the increase in patent citations and the number of patents in general. Using quality indicators (from the USPTO patent database) they discovered that in technological classes identified as GPTs, there is an above average increase of both patent citations and patent growth. This means, presumably, that GPTs have a considerable effect on inventive activities and suggests that the emergence of a new technological paradigm also affects the patent distribution. For our purposes this is important since it means that not only the focal technology benefits by creating linkages with others but an increase in patenting is visible on both sides.

An "evolution" of the concept of GPT is that of Key Enabling Technologies (KET). Actually, KETs are a particular subset of GPTs. Bresnahan & Trajtenberg (1995) while defining GPTs, explain that these particular technologies could have also the ability to *enable* other subsequent advances. In this sense they can open new possiblities for technical advances without offering final solutions.

The real identification of KETs was first put forward by the European Commission (EC), they identified six GPTs aimed at sustaining the competitiveness of the European industries in the world economy (European Commission, 2009). These are: nanotechnology, micro and nano-electronics including semiconductors, photonics, advanced materials and biotechnology. The European Commission (2009) claims that these technologies have unexpressed potentials that have to be exploited by the European industry, with the aim to use these KETs within smart specialization strategies. As affirmed by Montresor & Quatraro (2017) the main problem is that there was no theoretical foundation provided by the EC on how the KETs can be used as a driver for such strategies.

KETs have similar properties as GPTs (explained in the previous paragraph) but they can also be represented as the elementary units for the development of new processes, new products and new industries in the market (Montresor & Quatraro, 2017). This is a distinguishing feature between a GPT and a KET. In other terms, the sub-KETs are successful realizations of the main KET. One recent example was analysed by Akyildiz et al. (2016), who observed challenges that the wireless technology have to deal with in the introduction of the fifth generation (5G) of mobile communication. Wireless is seen as the KET while the 5G as the sub-KET. The development in the first is necessary to have the second, without these fundamental amelioration of the existing technology also the realization of the new one is at risk. This is the most important feature of a KET and it can be easily translated in the Knowledge Space (KS): the emergence of a KET can create sub-technologies that were previously not observable in the same KS. This will be used for the definition of BT since we expect that they are catalysts and help the development of other sub-technologies.

2.3 Knowledge Space

One of the more accepted theories among scholars in innovation economics is that the production of knowledge and technological change are important for economic advances, also at the regional level (Romer, 1986; Robert & Lucas, 1988; Scott, 2006). To measure the generation of knowledge in space and time many scholars use the concept of knowledge relatedness (Alstott et al., 2017; Boschma, 2015; Neffke et al., 2011; Boschma et al., 2013). Relatedness is frequently used to reconstruct the knowledge space, i.e. the network of interrelated technologies, of a region or an economy (Kogler et al., 2013).

Measuring relatedness between different technological fields is not a new concept. For example, Pavitt (1984) studied technical innovations in Britain to explain technological change and how it is influenced by knowledge flows from various sources. Another study by Jaffe (1989) used U.S. patent data to identify technologically related groups and showed that the success in terms of productivity of one firm is related to the investment in R&D in its technological neighbours. In both studies it is affirmed that innovation activities are more favourable in a context with connected or related fields (Pavitt, 1984; Jaffe, 1989). A similar concept is applied by Teece et al. (1994) who show that the growing number of activities performed by US manufacturing firms coincide with an increased coherence between similar industries. Breschi et al. (2003) develop a method to study technological relatedness through patent data, to understand diversification and firm performance.

Other researchers extend previous work on relatedness by including a spatial dimension. Hausmann & Klinger (2007) and Hidalgo et al. (2007) first studied relatedness with international trade data to understand the distance between different exported products. They propose that countries specialized in goods located in the most dense area of the "product space" can shift their production more easily to other products. This happens because the new knowledge needed for shifting is similar to their existing competencies. As a consequence, these economies are more diversified. For countries specialized in products in the periphery of the "product space" it is more difficult to shift production to other goods because they lack the respective competences so that they remain specialized.

Boschma et al. (2012) extend the work of Hidalgo et al. (2007) and show how Spanish regions diversify in different industries and how this process is affected by the pre-existing knowledge of the region. Other studies build on similar ideas to study the technological landscape of different regions. The study by Neffke et al. (2011) is based on the long term evolution of the Swedish technological and economic landscape. They show how industries that are related to those already present in the region can enter easier in the regional industry space. Quatraro (2010) show that the the knowledge stock embedded in Italian regions can shape the regional economic performance, triggering regional growth. Kogler et al. (2013) study how knowledge is distributed in different US cities using patent data. They discover that higher relatedness is present in smaller cities, while larger ones generate knowledge that it is more dispersed. They were the first to use the term Knowledge Space to identify the network based on relatedness between different technologies. More recently, Boschma et al. (2014) study how existing relatedness can affect the entering of a new technology in a city using US patent data. Finally, Balland et al. (2019) find that it is difficult for EU regions to diversify in complex technologies and propose that regions should increase their existing capabilities to assure competitive advantage.

This brief review of the literature shows that various data sources are used to measure relatedness. Measures using information on employee mobility (Neffke et al., 2011, e.g.) require micro-level data which is often unavailable or difficult to access and relate industries rather than technologies. Product exports (Hidalgo et al., 2007, e.g.) lack information on the technologies required for their production. Measuring relatedness with patent data has several advantages (Joo & Kim, 2010): patents are legal documents so all the data is gathered very carefully, they provide comprehensive information about the timing of the invention, technological classification, name of the inventors and applicants, they can address very long periods of time and almost every technological sector (beside software) (Verbeek et al., 2002; European Commission, 2003; Kogler et al., 2013). On the other hand, the use of patents is associated with specific problems that have to be taken into account: inventive activity is not fully covered because inventors can strategically decide whether to patent or not, there are differences in patenting activities geographically, technologically and firm-wise and some legal changes can influence patenting activity (Pavitt, 1985; Griliches, 1990; Khan & Dernis, 2006).

There are different methods to reconstruct the KS from patent data. Several studies classify and compare them and propose new ways on how to measure relatedness (Joo & Kim, 2010; Alstott et al., 2017; Yan & Luo, 2017). There are two main types of measures to capture relatedness between different technological fields: *Patent Reference-Based Measures* and *Patent Classification Based Measures* (Yan & Luo, 2017).

The *Patent Reference-Based Measures* use citation data to calculate the relationships between different technological classes (International Patent Classification or Cooperative Patent Classification). With this data it is possible to actually detect the cognitive "distance" among different classes (Alstott et al., 2017; Yan & Luo, 2017). Leydesdorff et al. (2014) and Kay et al. (2014) use a *cosine similarity index* to look into relationships in technologies that are cited or citing each other. This is useful to understand where the knowledge is generated and where it is applied.

The *Patent Classification-Based Measures* are based on the fact that patents are classified in different technological fields. These categories are provided by examiners from the issuing patent offices rather than by the applicants themselves. This information is used to calculate "distances" between technological classes based on co-classifications. The basic assumption is that the higher the frequency of two classes being assigned to single patents, the higher the proximity between these two classes (Yan & Luo, 2017). Several studies used this methodology and calculate a *co-occurrence matrix* where the frequency represented by the number in each cell is the actual number of patents that are combining two classes, represented by the corresponding column and row (Breschi et al., 2003; Kogler et al., 2013).

In this paper, we use two different approaches to reconstruct the KS. The first one is a simple co-occurrence matrix that, as explained above, represents the "proximity" between technologies by the number of patents that co-occur in two different classes. The second approach is based on the idea of Revealed Relatedness (RR) (Neffke & Henning, 2008). This introduces a probabilistic measure that allows us to compare the observed number of co-occurrences with the expected one. We employ two different methodologies to assess their suitability for our research question.

3 Bridging Technology Definition

GPTs as well as KETs are identified by top-down approaches. These technologies have first been recognized by scholars of economic history as being responsible for growth in regions or countries (Landes, 2003). Subsequently, evolutionary economists identify these technologies as GPTs because of their particular characteristics (Bresnahan & Trajtenberg, 1995). Building on the definitions of GPTs and KETs, we try to identify technologies that are sources of growth for single regions. In this sense, we do not search for specific, already identified technologies in the regional KS. Instead, we search for technologies that have similar characteristics as GPTs and KETs (mainly *pervasiveness*) in the regional KS and and analyze the dynamics of these important and presumably growth driving technologies. Assuming that knowledge is sticky and a particular milieu is formed in specific regions, we expect that regions have their particular technological characteristics which can change over time (as a new paradigm emerges also a new bridging technology can emerge in the analysed region).

In the following, we define the concept of Bridging Technology (BT). Quite generally, it is defined as a field of technology that connects otherwise more distant technologies within a KS. This is a shared characteristic with GPT and KET, what differs is that there is no ex ante identification of a BT but it is rather defined by its function within the KS. As such, there can be different BTs in diverse KS which depends on the embedded characteristics of the area itself. The function of the BT is important since it affects the cohesion of the KS. The literature about KS coherence helps us to understand how these technologies can be important for the structure of the network. Quatraro (2010) states that the understanding on how two nodes (technologies) are associated can provide valuable information on how the KS in a particular region is structured. We expect that these nodes which occupy central positions in the network are important for its performance since they establish potentials for cross-fertilization in the KS by connecting otherwise more distant technologies.

We define bridging technologies based on two alternative concepts of centrality of a technology (node) within the KS (Graf, 2012). In the first approach, we define BTs as those technologies that serve as catalysts in the KS network by being connected to many other technologies (degree centrality). In the second approach, we define BTs as technologies that connect two different parts of a KS that would either be unconnected or only at longer distances (betweenness centrality).

Figure 1 shows a graphical representation of both definitions. The first one (Figure 1a) represents a BT (red node) that is connected to many other technologies and is at the center of the network. In the second definition (Figure 1b) the red node does not have most connections, but it establishes a link between two otherwise separated parts of the KS.

(a) Definition 1 based on the concept of degree centrality

(b) Definition 2 based on the concept of betweenness centrality

Figure 1: Bridging Technology Definitions

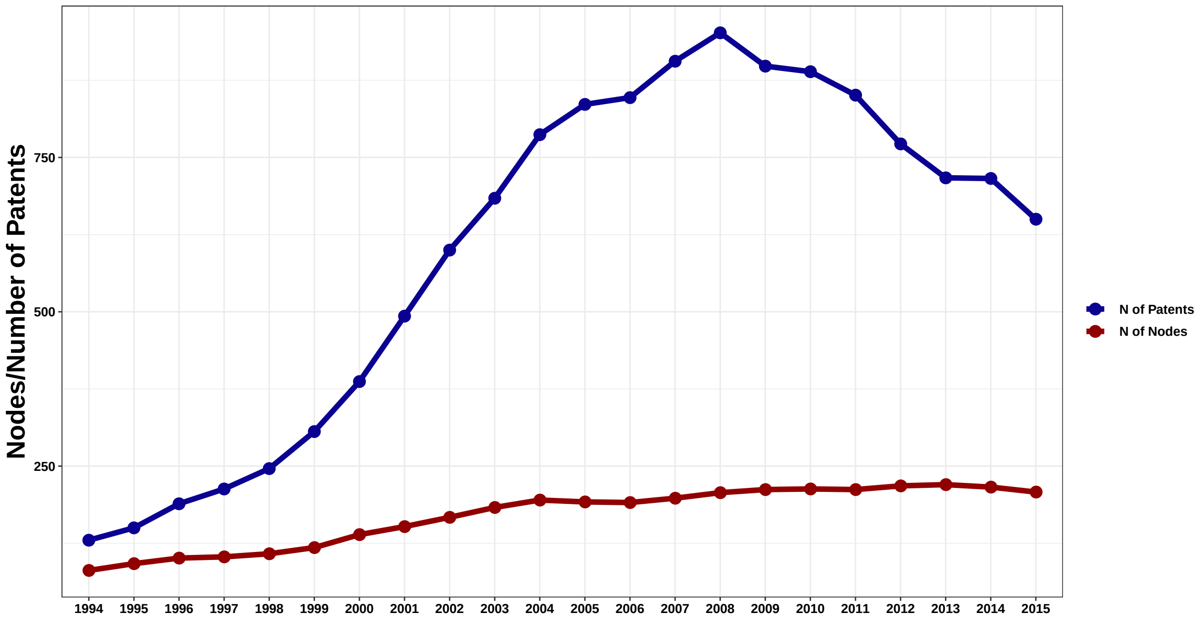


Figure 2: Number of Patents and Nodes in Jena KS

4 Methodology

4.1 Data

We use the OECD, PATSTAT database, Autumn 2017 to select all patent applications with at least one inventor or applicant located in Jena with priority 1990 to 2015. As regional boundary, we use the Labour Market Region (LMR). This comprehends not only the city of Jena but also its surrounding area where commuters live. The knowledge spaces are reconstructed for 5 year moving windows, so that the KS for the year 1994 is composed of patents filed between 1990 and 1994.

For the technological (co-)classification of patents, we rely on the Cooperative Patent Classification (CPC). The CPC classification was developed in cooperation between the European and US Patent offices to replace the International Patent Classification (IPC) (Leydesdorff et al., 2017). The CPC classification is comparable to the IPC at four digits level, however, the process of re-classification from IPC to CPC allowed adding new classes.

We decided to use the CPC classification for several reasons. It seems to be more consistent over time, it allows us to identify more linkages between technologies via co-occurrences, and it includes the section "Y" that identifies new technological developments (Leydesdorff et al., 2017). These are principally classes connected to nanotechnology and climate change mitigation (Scheu et al., 2006; Veefkind et al., 2012). We exclude two of the Y subclasses from our analysis since they do not describe sufficiently homogeneous technologies [1].

Figure 2 shows the number of patents and distinct CPC4 classes that constitute the Jena KS for the observation period. There is a pronounced increase in the number of 4-digit CPC classes (nodes) until 2004 and a flattening afterwards with a more or less constant number of classes during the final periods. The number of patents reaches its maximum in 2008 and then constantly declines.

In the next sections, we describe how we reconstruct the knowledge space of Jena (and of the other German regions). More specifically, we use two different methods based on the co-occurrence matrix and on the relatedness matrix.

4.2 Knowledge Space reconstruction

The basic KS reconstruction follows a co-occurrence method. In this case, the connection between two technology classes is formed whenever a patent is co-classified in both of them. The more frequently the connection is repeated in one period, the closer two CPC classes are in the KS (Nesta & Saviotti, 2006; Graf, 2012). The results for the co-occurrence methodology are provided in subsection 4.3 (with the Bridging Index) and in the appendix A.

For the relatedness matrix, we use a similar approach as the revealed relatedness method explained in detail by Neffke & Henning (2008). They develop a strategy to distinguish relations between different industries from product portfolios. They use information from product portfolios of plants and assume that the production of two goods in the same factory indicates a relation between the two industries to which the products are assigned. The justification for this assumption is that they apparently share, at least partly, the same inputs and production processes. Our approach is similar, since patents that draw on or are relevant for two technologies (CPC classes) indicate a relatedness between these technologies. With an increasing number of patents assigned to two classes, relatedness between them increases. This co-occurrence is only the first step in the revealed relatedness method. In the second step, we use a probabilistic measure to compare actual with potential co-occurrences. If we assume that knowledge spaces on different levels are interrelated, the KS of the world influences the national ones and the national KS affects the regional ones. By reconstructing the world KS, it is possible to understand if a region is following the global trends in terms of relatedness. We assume that a frequent combination of two technologies in the global KS positively influences the likelihood of this edge being repeated in the studied region.

To calculate relatedness between each CPC 4 digits technology pair, we employ the Otsuka-

[1] Y10S (GENERAL TAGGING OF NEW TECHNOLOGICAL DEVELOPMENTS; GENERAL TAGGING OF CROSS-SECTIONAL TECHNOLOGIES SPANNING OVER SEVERAL SECTIONS OF THE IPC) and Y10T (TECHNICAL SUBJECTS COVERED BY FORMER USPC CROSS-REFERENCE ART COLLECTIONS AND DIGESTS) are special classes that include many different technological fields due to the harmonization from IPC to CPC classification.

Ochiai coefficient C_{ij} (Ochiai, 1957) to normalize the observed co-occurrences with the size difference among technologies.

$$C_{ij} = \frac{c_{ij}}{\sqrt{c_i \cdot c_j}} \tag{1}$$

Where c_{ij} is the number of co-occurrences between two technologies (i and j). The square root of c_i and c_j represents the geometric mean of the size of the two technologies (occurrence of i multiplied by the occurrence of j). The result of this equation can vary between 0 and 1. If the coefficient is 0 then there is no overlap, i.e. no patent in i also contains j, while if it is 1, every patent in i also contains j. The calculation of this coefficient is performed on world (C^w_{ij}) and regional (C^r_{ij}) levels. The difference between regional and world levels is used to reconstruct the KS. If the difference is positive ($C^r_{ij} - C^w_{ij} > 0$) then the region has more combinations than expected on the world level, otherwise if the difference is negative, the region combines the two technologies (i and j) less than expected. These differences define the edges in the network that represents the regional KS in each considered period with 5 year moving windows.

4.3 Two Indicators for Bridging

Inspired by the first definition of BT, we calculate the "Bridging Index" based on a simple co-occurrence matrix. It is a continuous indicator taking into account the degree to which any technology fulfils a bridging function. This measure is composed of two different parts: a diversification index (DI) and the normalized sum of co-occurrences.

The DI is based on the Herfindahl-Hirschman Index (HHI), which is widely used to explain concentration, e.g. in the banking sector (Acharya et al., 2006; Stiroh, 2004) or in markets and income (Rhoades, 1993). Since the HHI is a measure of concentration, the DI is simply the inverse of the HHI, to measure diversification (Duranton & Puga, 2000). The idea is that a technology is diversified, the more it is connected with different technologies.

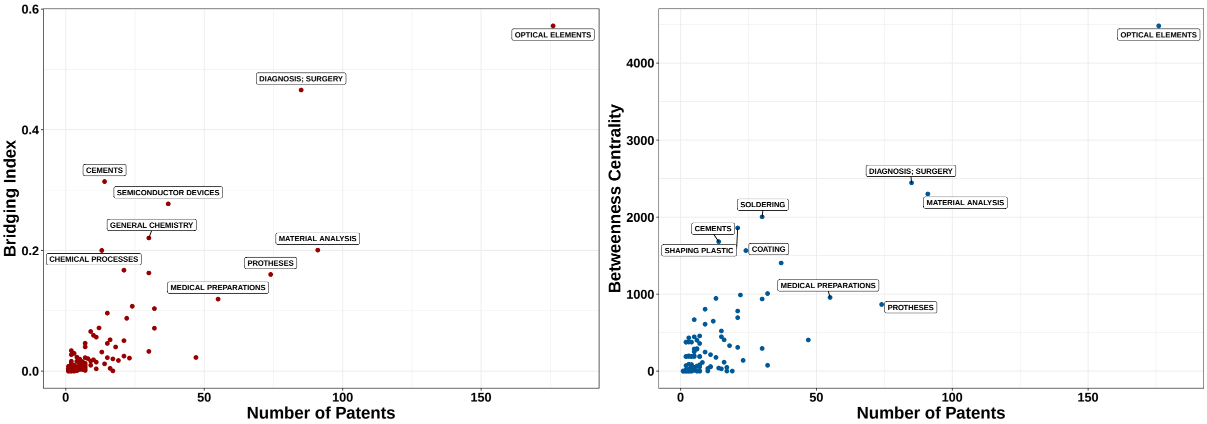
$$DI_i = \frac{1}{\sum_{j=1}^{n} s_{ij}^2} \tag{2}$$

In equation 2, s_{ij} is the share of patents co-classified between two CPC classes (i and j) with respect to the total number of patents belonging to CPC class i. The Bridging Index (BI) is then defined in equation 3.

$$BI_i = DI_i \cdot \sum_{j=1}^{n} normco_{ij} \tag{3}$$

We take the product of the DI and the normalized sum of co-occurrences ($normco_{ij}$). The co-occurrences between two technologies (i and j) are normalized by dividing it by the sum of all co-occurrences in one period so that it is independent of the number of patents when comparing across time or regions. As such, the BI accounts for the number and distribution of co-occurrences of a technology. A change in this index for a CPC 4 digit class indicates increasing or decreasing importance of the node in the network.

As an alternative indicator for bridging, we use the second definition of BT to understand



(a) Bridging Index and Number of Patents **(b)** Betweenness Centrality and Number of Patents

Figure 3: Correlation between the bridging measures and the number of patents of each 4-digit CPC class in Jena for a representative year (2010).

which nodes hold a central, bridging position within the KS network. The calculation of betweenness centrality (B_i^C) for node i is provided in the following equation 4.

$$B_i^C = \sum_{j<k} \frac{g_{jik}}{g_{jk}}, \forall i \neq j, k \tag{4}$$

With j, i, k as distinct nodes, g_{jk} is the number of geodesics between j and k and g_{jik} is the number of geodesics between j and k passing through i (Wassermann & Faust, 1994).[2] We use a weighted version of betweenness so that high relatedness edges are shorter than edges with low relatedness.

Table 1 shows the descriptive statistics and a correlation analysis of the different measures. As expected, the correlation between BC, BI and the number of patents is quite high. This suggests that a class with a high number of patents has also a high score in BC and BI. However, the importance of a technology in the KS is not completely explained by the number of patents. This is even clearer in figure 3, where, for Jena in the year 2010, both measures are plotted against the number of patents. Unsurprisingly, *Optical Elements* has high values for BI, BC and a high number of patents. However, classes like *Cements*, *Shaping Plastic* (in BC) and *Semiconductor Devices* (in BI) score high in one of the presented indexes despite their low number of patents.

Table 1: Descriptive Statistics and Correlations in Jena

	Statistics							
	Descriptive Statistics					Correlations		
	Mean	SD	Minimum	Maximum	N	Brdg Ind	Bet Cent	Pat
Bridging Index	0.028	0.079	0	0.969	3350	1	\	\
Betweenness Centrality	142.162	399.264	0	4922.000	3726	0.74	1	\
Patents	6.259	14.454	1	208.000	3726	0.68	0.82	1

[2]We calculate node betweenness centrality with the igraph package for R (R Core Team, 2018; Csardi & Nepusz, 2006).

5 Comparing Bridging Indicators for the Jena KS

In the following, we present an analysis of the Jena KS according to both measures for bridging technologies presented above.

5.1 Bridging Index (BI)

In figure 4 we present the results for changes in the BI, based on the co-occurrence matrix, for the highest ranked CPC 4 classes in Jena. We rank each CPC 4 class for each period (the one with the highest BI is marked with 1). We only display the CPC 4 classes that are at least 4 times (from 1994 to 2015) among the top 10 in the ranking. Thereby, we identify technologies that are continuously relevant for the KS and exclude outliers which might be important technological fields only for a short period due to one patent assigned to many CPC classes. The ordering of classes is from the highest median rank throughout all years (top of the heat map) to the lowest median rank (bottom). For ease of interpretation and readability, we provide simplified names of the CPC 4 classes rather than the official ones (e.g. G02B is *Optical Elements* instead of "OPTICAL ELEMENTS, SYSTEMS, OR APPARATUS".

Only three technologies (*Optical Elements*, *Material Analysis* and *Chemical Processes*) are continuously among the top 15 bridging technologies in the Jena KS. *Medical Preparations* is in top spots at the beginning and at the end of the period, it is only losing some positions in some years in the middle. Some technologies appear in top positions at the beginning but become less important over time: *Chemical Processes*, *Acyclic Compounds*, *General Chemistry* and *Macromolecular Compounds*. Another group of classes emerges as BTs by the end of the observation period: *Shaping Plastic*, *Cements*, *Soldering*, *Diagnosis; Surgery* and *Semiconductor Devices*. *Prothesis* and *Sterilising Material* have a high index only during the middle of the period. One of them fulfills a bridging function only during the early and later periods: *Glasses Composition*.

5.2 Betweenness Centrality (BC)

In figure 5, we present the results for Jena based on the rankings of betweenness centrality in the relatedness matrix (using the same method of display and assumptions for selecting the displayed technologies as in figure 4). There is more turbulence when using betweenness centrality than with the BI above, so that the interpretation is less straightforward.[3]

The two technologies identified as BTs throughout the whole period are as in figure 5: *Material Analysis* and *Optical Elements*. *Measuring* and *Chemical Processes* are dominant in the beginning but then lose positions. Five classes become important by the end of the period: *Soldering*, *Semiconductor Devices*, *Emissions Reduction*, *Shaping Plastic* and *Coating*. *Climate Change Mitigation* is only important during the middle of the considered time frame. Finally, three classes lose important positions during the middle but then recover by the end of the time frame: *Diagnosis; Surgery*, *Medical Preparations* and *Cements*.

Two BTs in Jena are identified by both measures: *Optical Elements* and *Material Analysis*.

[3] In Appendix A we display the heat map with betweenness based on the co-occurrence matrix. Since the results are quite similar, the larger turbulence is not caused by the method of reconstructing the KS but by the methodology used to identify BTs.

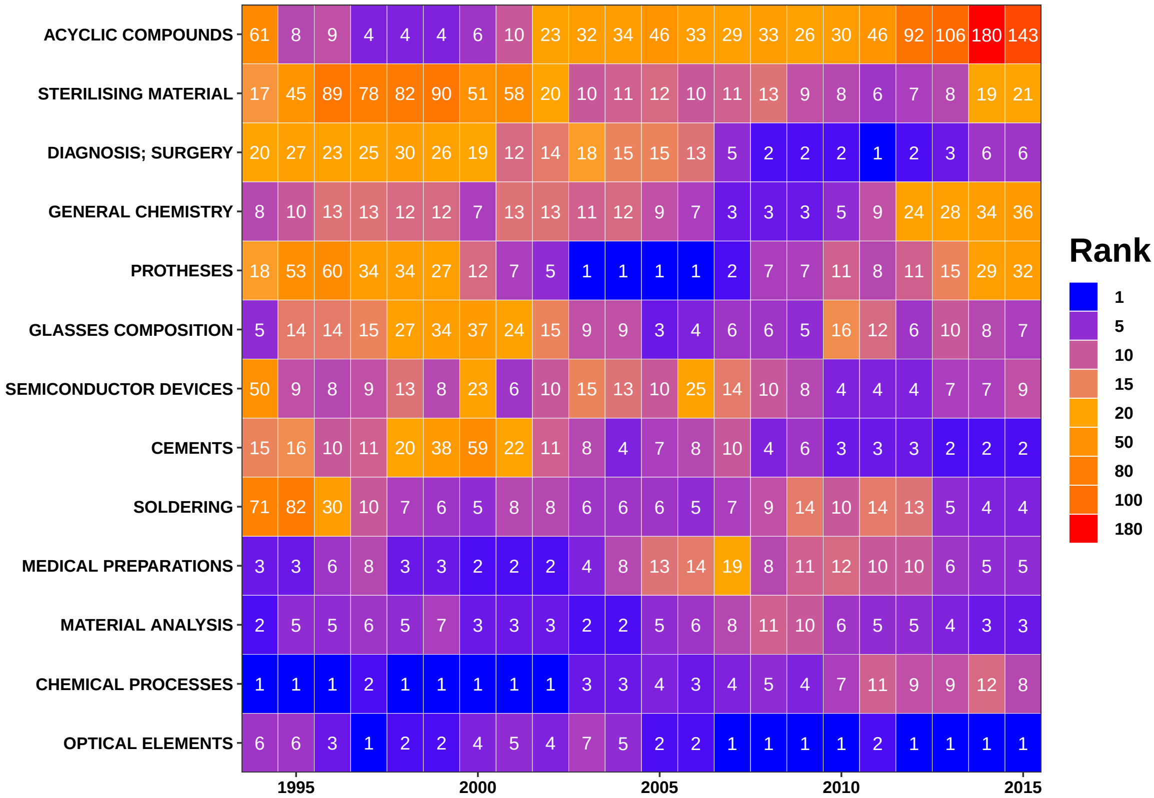


Figure 4: Bridging Index Ranking in Jena (1990-2015)

This means that throughout the whole period they have the capacity to connect with many other technologies (as indicated by the BI measure) and are often on the shortest path between other technologies (BC measure). This result is not surprising since some large international companies in Optics and Instruments, such as Carl Zeiss or Jenoptik are located in Jena.

For the remaining part of the paper we will use BC as the bridging indicator. Even if the BI is more intuitive and less correlated with the number of patents, it can be misleading in some points. First, the BI index is based on a simple co-occurrence matrix which does not fully capture the relatedness between different classes (Joo & Kim, 2010; Yan & Luo, 2017). We believe that introducing a probabilistic measure which compares the actual with the expected number of co-occurrences better captures the relatedness between different technologies. Second, BC is a measure that takes the structure of the whole KS into account and not just direct connections as the BI. Third, as shown in Figures 4 and 5), the BC index puts a stronger weight on classes with a higher number of patents. This gives a better representation of the classes that are really important to the regional KS. This holds true for the Jena case where *Optical Elements* and *Material Analysis* appear strongest throughout the whole period (1990-2015) with BC but not with the BI. Since we know that in Jena there is a strong presence of multinational companies specialized in *Optics* and *Material Analysis*, we rely on the BC index.

6 Revealed Bridging Advantage (RBA)

In this section we propose an additional index to perform regional and technological comparisons in Germany. While BC can be used for comparisons among technologies within a regional KS

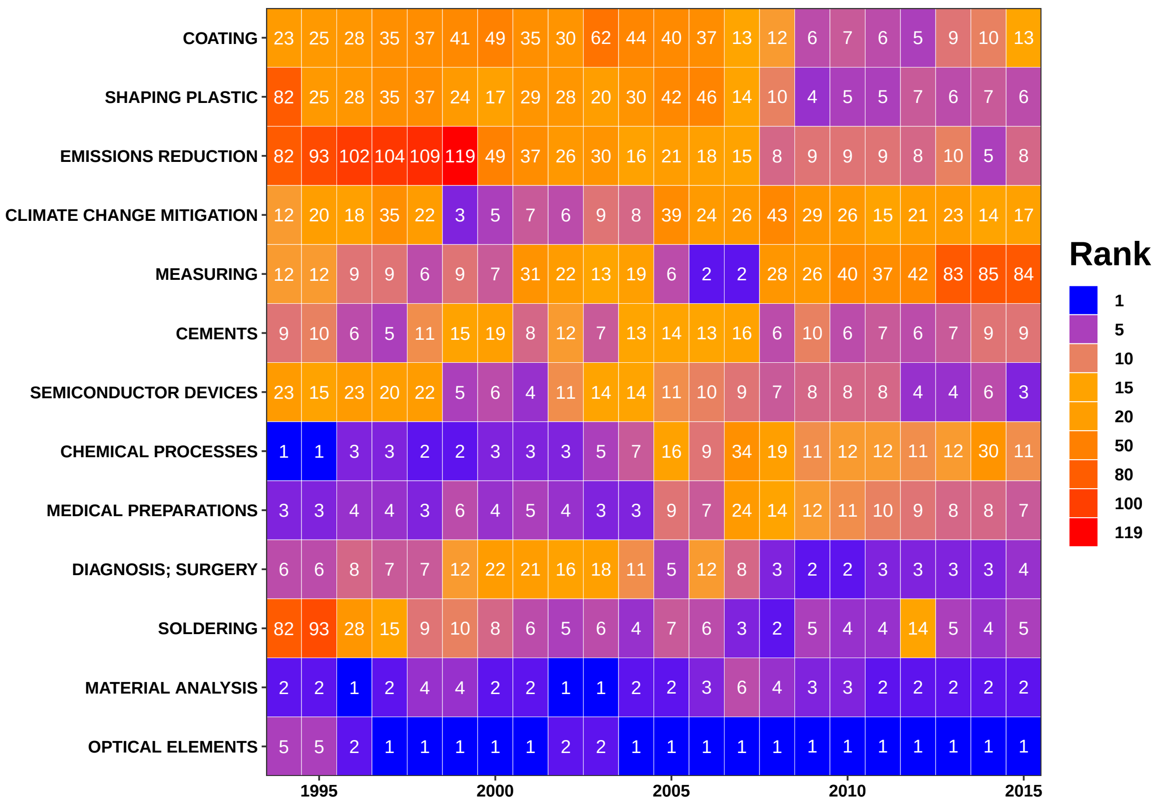


Figure 5: Betweenness Centrality Ranking in Jena (1990-2015)

it is not applicable when comparing the same technology observed in different regions. The idea here is to create a benchmark for each technology that shows if a region performs better in embedding a specific class compared to all other LMRs in Germany (6.2) and which technologies are increasingly well embedded across regions (6.3). In addition, we exemplify the application of the RBA measure by taking a deeper look at developments within the KS of Jena (6.4).

6.1 Defining Revealed Bridging Advantage (RBA)

Following the work of Hidalgo et al. (2007) and Boschma et al. (2013) on relatedness in countries and regions, we propose an alternative use of their proposed measures. In their studies they were able to discover how the relatedness of two technologies in one region/country is different from the relatedness measured in all the other regions/countries. This is important because it permits to track the technological development of regions over time and allows to predict the future technological development of a region. Instead of using trade data, we use the betweenness centrality measures to compare technological developments across German regions. This is done to understand if the observed technological trends are Jena specific or if they are visible in other regions as well.

We propose the Revealed Bridging Advantage (RBA) as a measure inspired by the Revealed Technological Advantage (RTA) index (Soete, 1987), applied on the BC measure. In the following, we use an aggregation of CPC 4 digit classes as provided by Schmoch (2008). The aggregation is useful for two reasons. First, if a region is highly specialized in few CPC 4 digits classes that belong to the same Schmoch category it would be easier to identify the entire group as a BT. The second reason is more technical. The CPC 4 digit classification is too fine-grained when applied on the level of LMRs in Germany. In many regions, we can only observe a subset of these classes and some are only present in few periods so that the KS appears more turbulent than it actually is.

For this aggregation, we calculate SBC_{rst} as the sum of the BC values of all CPC classes belonging to each Schmoch class:

$$SBC_{rst} = \sum_{j \in s} BC_{rjt} \tag{5}$$

Where, r is the region, j is the CPC 4 digit class, t is the year and s is the Schmoch class. The RBA is then defined as follows:

$$RBA_{rst} = \frac{SBC_{rst} / \sum_{r=1}^{n} SBC_{rst}}{\sum_{s=1}^{m} SBC_{rst} / \sum_{r=1}^{n} \sum_{s=1}^{m} SBC_{rst}} \tag{6}$$

Where s is a Schmoch technological field (out of m) and r is a region (out of n) at time t. RBA_{rst} ranges between 0 and $+\infty$. An $RBA_{rst} = 1$ means that the level of bridging of a technology in a region is the same as on the national level. An $RBA_{rst} < 1$ indicates that the technology serves the bridging function in the respective region to a lower extent than in the rest of Germany. Finally, an $RBA_{rst} > 1$ means that the region is above the general technological bridging capacity in that specific technology.

6.2 Regional RBA dynamics

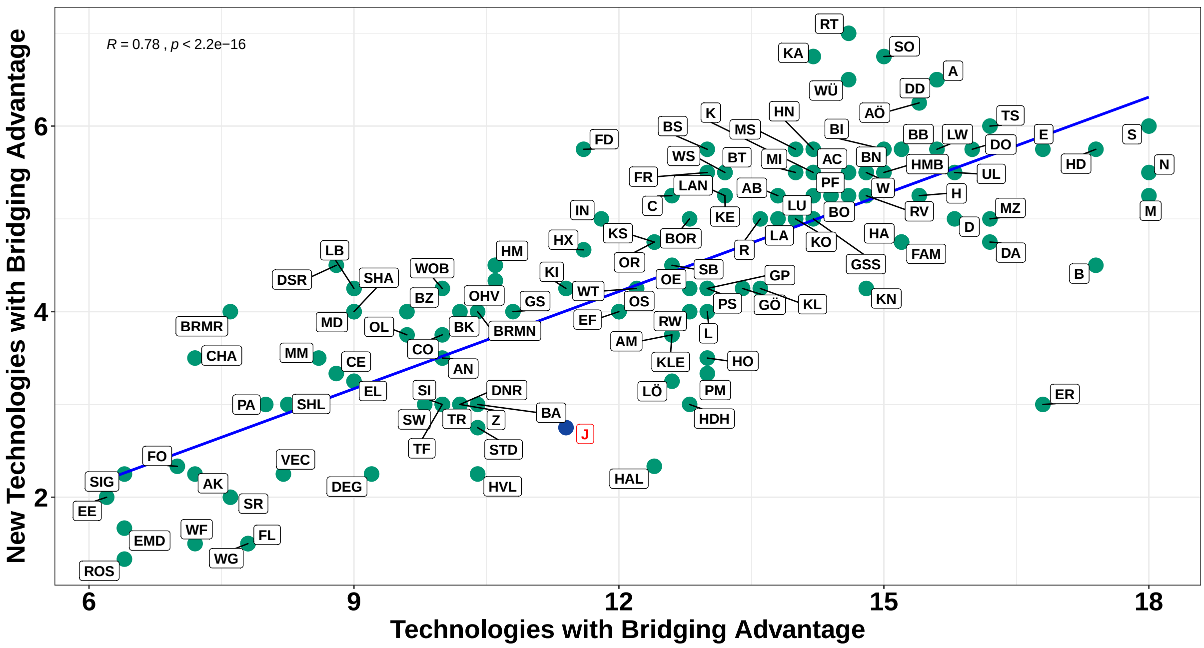


Figure 6: Relation between the number of technologies with an RBA > 1 at time t and the number of new technologies with an RBA > 1 at time $t + 5$ in German LMRs (1995-2015 average; 5 year intervals)

Following the work of Boschma et al. (2013) on Spanish regions, we explore how the Jena KS performs relative to other German regions in terms of the RBA. For each German region, we compare the average number of technologies for which the RBA was ≤ 1 in the 5-year periods

1995, 2000, 2005, 2010 and 2015 but developed an RBA $>$ 1 five years later with the average number of technologies that in the same years experienced an advantage (RBA $>$ 1). To put it more simply, we count for each region, how many technologies move from a revealed bridging disadvantage to an advantage. This should give us an indication about the performance of regions in terms of developing bridging advantages we analyse how Jena is positioned in this context.

Figure 6 shows that there is a positive relationship between the number of technologies that have an advantage with the number of technologies in which the region develops an RBA five years later. Therefore, regions that show a higher number of RBAs are also the ones that have better capabilities to develop an advantage in the future. The fact that these regions are dynamic eases the incorporation of new technologies to create a better interconnected system. Regions that are below the regression line acquire less RBAs over time than expected. While the ones above, on average, acquire more RBAs than expected. The former regions are technologically more stable, whereas the latter regions are technologically more dynamic.

Jena belongs to the group of stable regions which develops few new Bridging Advantages. This indicates that the KS of Jena maintains RBAs in the same technologies over this long period, a result that is in line with our findings above, that show that the core technologies in the KS are related to optics and material analyses. When looking at the results for other regions, we find that the large regions with a high number of RBAs, such as Stuttgart (S), Munich (M), and Nuremberg (N), develop fewer new RBAs than expected. On the other hand, there are some regions with a smaller number of RBAs that develop many new RBAs (RT = Reutlingen, KA = Karlsruhe, SO = Soest, WÜ = Wuerzburg, DD = Dresden, A = Augsburg), i.e. their KS is highly dynamic. Overall, these results show that some regions that do not patent a lot are still capable of introducing more BTs than some larger regions (the list of regions is reported in Table 4). As to whether a more or less dynamic KS is a good indicator for economic development, there is no simple answer. While a rigorous analysis of its causes and effects is beyond the scope of this paper, it should be clear that KS dynamism in terms of RBA development is not an end in itself. Rather, it shows that a region might respond to structural change and thereby transforming its KS. A stable KS can also indicate success as some examples of small specialized regions show. Erlangen (ER) or Jena (J) are well below the average RBA development but are nevertheless considered technologically highly developed and experienced substantial economic growth during the past decades.

6.3 Technological RBA dynamics

In addition to regional differences we apply the concept of RBA to technologies to analyse their differential dynamics within the German and regional KS. To identify particularly well embedded technologies, we build an indicator that takes into account how many regions for each technology had an $RBA > 1$ in two different time periods (1995 and 2015). In figures 7a and 7b, this measure is compared to the BC (aggregated by IPC 4 digits classes) for the whole German KS for each Schmoch category in the same two periods. This allows us to understand which technologies became more important in the German KS both regionally and nationally. A large number of regions with an $RBA > 1$ in a particular technology implies a greater regional diffusion in the German KS. If the aggregated BC is high it means that the technology is well embedded in the whole national KS. Since we take all German patents into consideration, it takes time to observe changes in the system and we chose to compare two periods with a 20 year difference. Not surprisingly, in both periods, Betweenness Centrality in the German KS is positively related with our regional diffusion measure (Number of Regions with $RBA > 1$). In the period 1995, *Chemical engineering* is at the center of the German KS while *Other special machines* is most widely diffused. Some technologies are important for many regional KS despite a lower bridging relevance in Germany (e.g. *Macromolecular chemistry* or *Materials*).

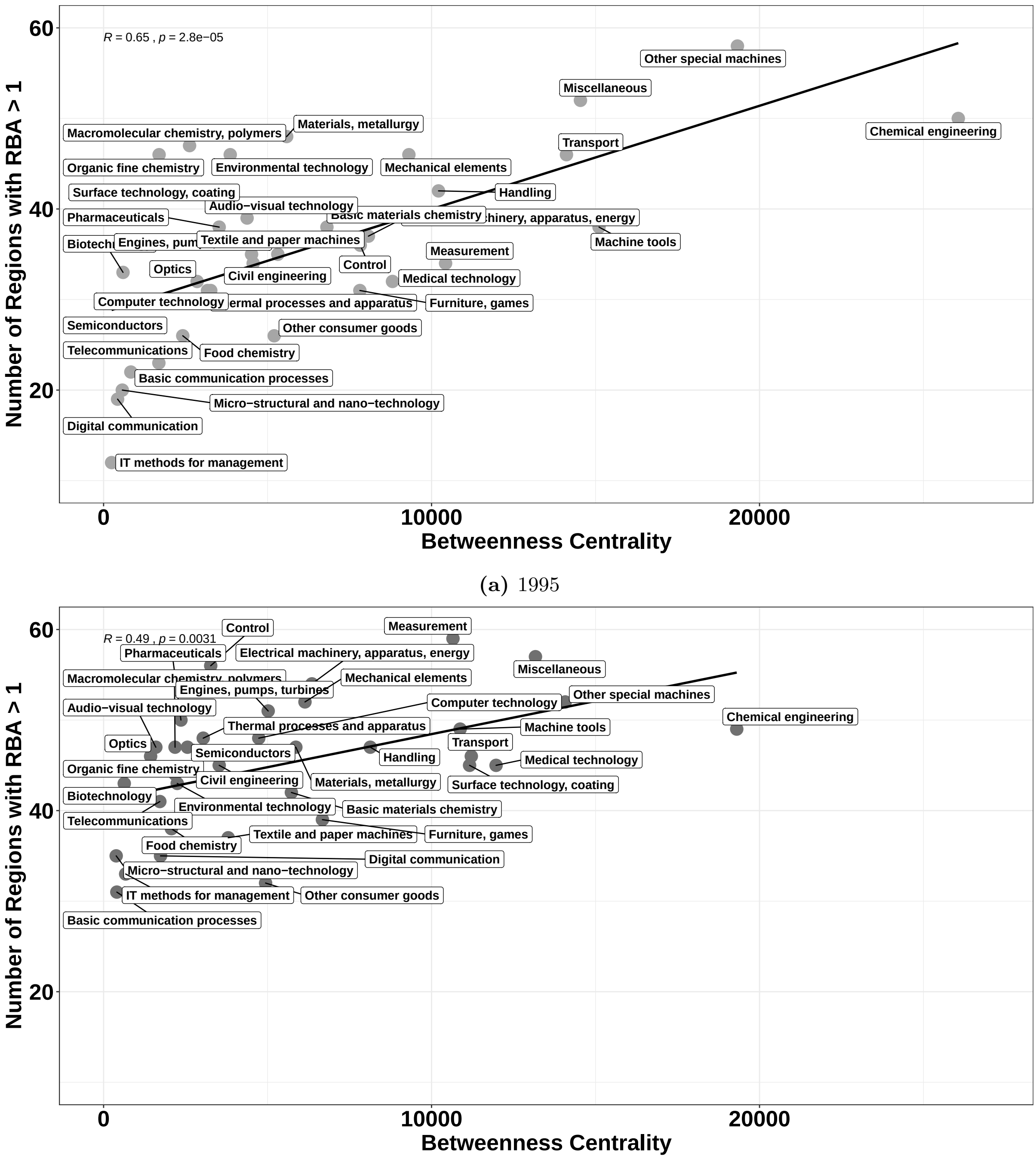
Comparing figure 7a and figure 7b most technologies increased the number of regions with an $RBA > 1$. This means that, generally, the technologies are more diffused regionally in the German KS. Nationally, we observe a BC reduction for technologies that were particularly central in the 1995 period. The increased local diffusion could be explained by the fact that there is a general trend towards the increasing of the division of labour, meaning that the average team size is increasing putting together people with different backgrounds. This is reflected also on the KS with an increased possibility of interaction among different technologies (Wuchty et al., 2007).

In figure 8, the dynamics for selected technologies with notable shifts are displayed. These nine technologies can be divided into three different groups based on their long term development. The first group consists of technologies that were strong both in local diffusion and national embeddedness in 1995 (*Transport*, *Other special machines* and *Chemical Engineering*). All three of them experienced a reduction in the national BC and a slight decrease in the number of regions that have an $RBA > 1$ meaning that they became slightly less diffused locally and less embedded nationally. The second group is composed of technologies positioned in the central part of figure 7a (*Electrical machinery, apparatus, energy* and *Control*). Both increase in terms of the number of regional bridging advantages but with a reduced national BC. Therefore, these technologies experienced an increased local diffusion with a reduction of the national embeddedness. The third group is represented by technologies that in 1995 have a medium-low BC and number of regions with $RBA > 1$ (*Semiconductors*, *Computer technology*, *Medical technology*, and *Measurement*. These four technologies have both a higher number of regions with bridging advantages and a raise in BC in 2015. Thus, this means that they are becoming more diffused locally and have a higher embeddeddness nationally.

Overall, it is interesting to observe how technologies move within both regional and national KSs. It provides insights about which technologies are of increasing relevance for the German KS and which are loosing importance in connecting technology fields. It is noteworthy that there are no technologies that become more embedded within the German KS without an increase in regional RBA diffusion. Apparently, the process of increasing embeddedness is not driven by single regions but rather a geographically dispersed phenomenon.

6.4 RBA in Jena

In our final application of the RBA, we come back to our case study of the Jena KS. To observe long term technological changes in the KS of Jena, we compare the RBAs in 1995 and in 2015. This can help us to understand if some technologies emerged as driving, in the sense that they are specifically from Jena and not elsewhere, the bridging process and/or if the ones that were driving it at the beginning are not important in the Jena KS anymore. It also helps us to assess



(a) 1995

(b) 2015

Figure 7: National BC versus the number of regions with $RBA > 1$ for each technology in two different time periods

whether the BTs identified in the previous section are Jena specific.

In figure 9, the RBAs for all technologies are presented. There are several technologies which have a continued higher bridging capacity in Jena than in Germany: *Optics*, *Pharmaceuticals*, *Measurement*, *Microstructural and Nano-Technology*, *Medical Technology*, and *Materials, Metallurgy*. These classes represent the core activities of Jena with big international firms, such as Carl Zeiss AG, Jenoptik AG, and Schott AG located in the area. In this group, only *Optics* shows an increase in relative bridging, while all others show a decline, because the RBA value is increasing in 2015. This suggest that a technology that is already established in Jena (like *Op-*

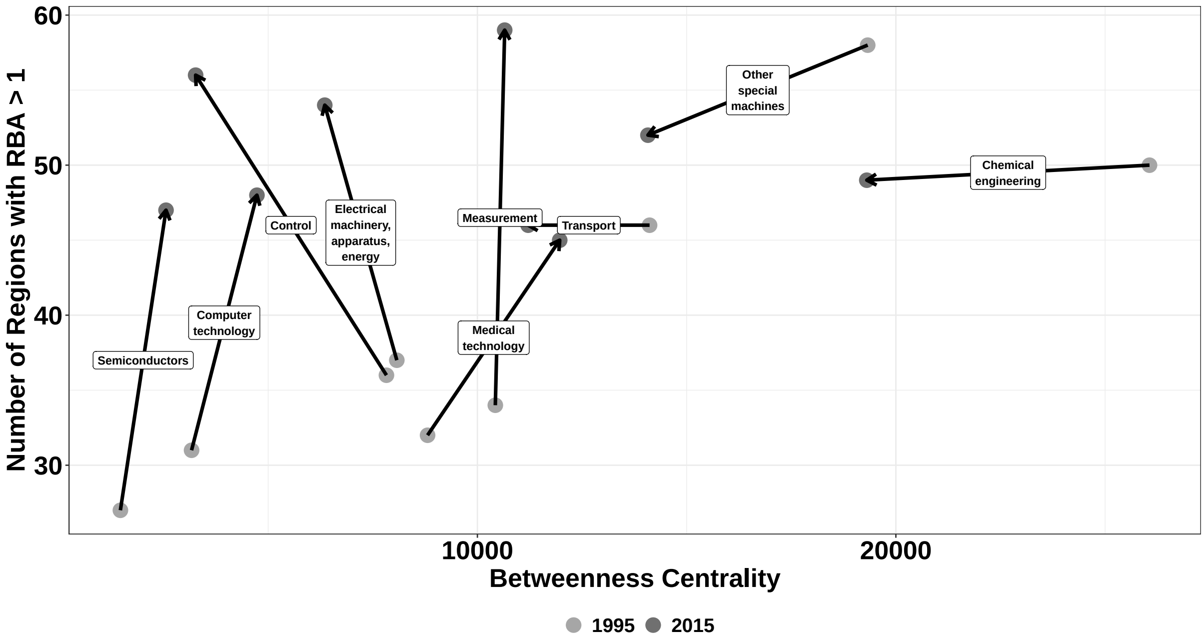


Figure 8: National BC versus the number of regions with $RBA > 1$ for each technology in two different time periods (comparison on selected technologies)

tics is) is even reinforcing its position in the KS by connecting many other fields. The stability of this technological core is also responsible for our observation of relative stability of the Jena KS (see section 6.2 and figure 6). *Semiconductors*, *Audio-Visual Technology*, *Machine Tools*, and *Computer Technology* are the classes in which Jena developed an RBA. In 1995, they were bridging less in Jena than in the average of all German regions but more in 2015. *Machine tools* was not even present in Jena in 1995 while in 2015 it has a Bridging Advantage. Other technologies show a decline in relative bridging passing from an $RBA_{ist} > 1$ to an $RBA_{ist} < 1$. These are: *Organic Fine Chemistry*, *Chemical Engineering*, *Macromolecular Chemistry, Polymers*, and *Biotechnology*.

Overall, the KS in Jena is relatively stable and if we compare the technological landscape of Jena with the other German regions, we observe that Jena does not develop so many new RBAs over time. We also find that the Jena KS evolves by embracing new technologies that were not important 20 years ago. These new technologies are mostly related to Information and Communication Technologies (the presence of the class *Semiconductors* reveals that Jena is also involved in the production of elements for the computer industry) and creation of machines for the production of other goods. Other classes lose their important bridging feature, and these industries, which were once quite crucial for Jena do not seem to be anymore. A particularly interesting case is *Biotechnology*: Jena won the BioRegio contest and received funds for projects related to BioInstruments. It seems that the core *Biotechnology* was progressively abandoned in favour of other technologies related to the "instrument" part.

7 Conclusion

Technologies differ in their potential to spur economic growth by affecting developments in related fields of technology and economic activity. Such technologies have been labelled as General

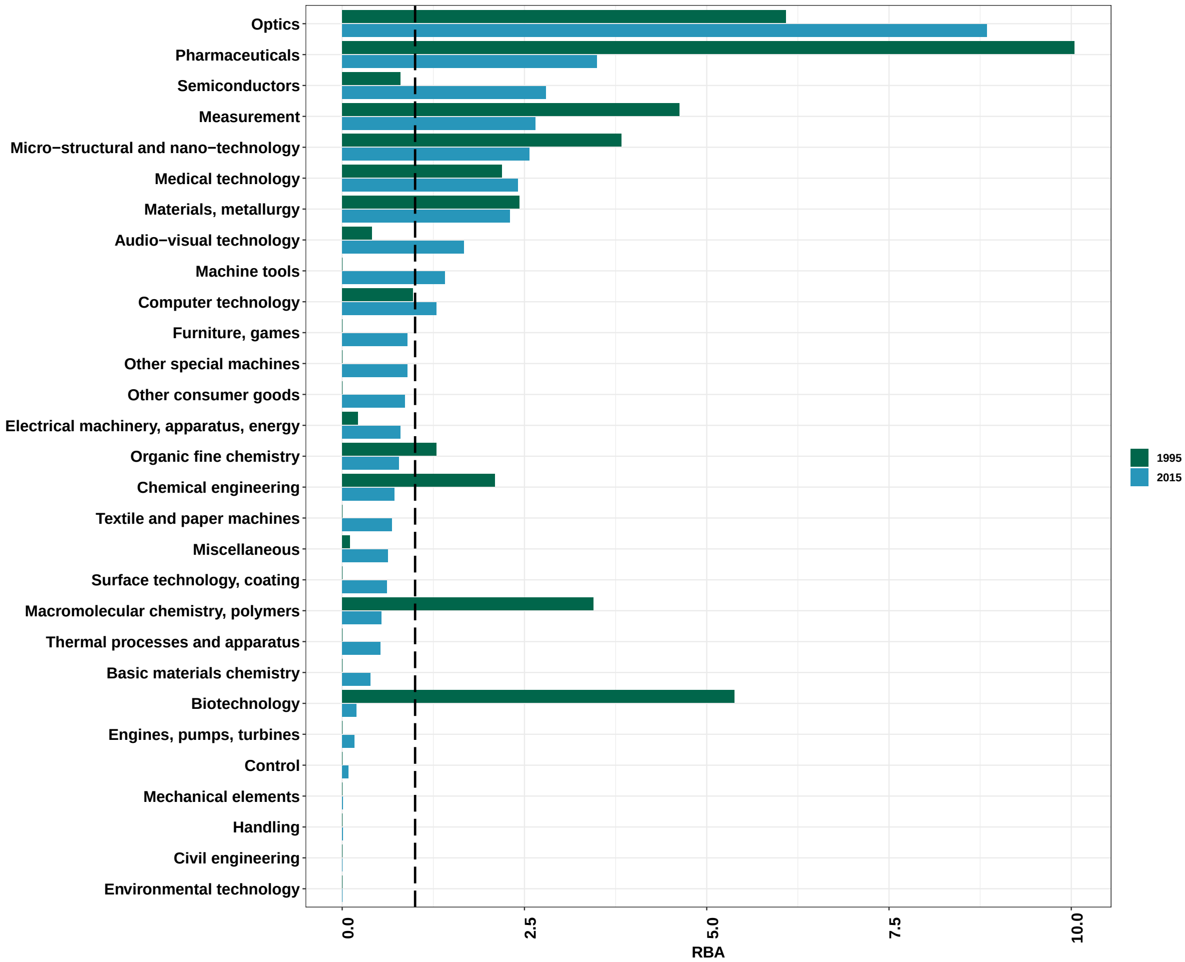


Figure 9: RBA comparison in two different periods of time (1995-2015)

Purpose technologies or Key Enabling Technologies. In the context of the knowledge space, i.e. the network of related technologies, they serve a bridging function by establishing links between technology fields. We contribute to the scarce literature on bridging technologies and knowledge spaces. Both from a theoretical and methodological point of view, we provide analytical tools to measure BTs and their evolution over time. We apply these tools by studying the case of Jena within the German context, where we could observe a process of substitution of previously important technologies in the KS over the last 20 years with some emerging technological trends. This framework could be applied to other regions but also used for comparative studies.

According to the reviewed literature, a Bridging Technology has to be connected with many other technologies and has to be important for the structure of the knowledge space. With these indications, we develop two definitions, one concentrated on the number of connections within the KS (BI), the other one based on the structural position of a technology within the KS (BC). Based on both definitions, we developed two different indicators to detect BTs and apply them to analyse the Jena KS. We choose Jena as a case study region since it is a strong patenting region. Due to its success in the BioRegio contest, we know about some recent technological changes that should affect the KS. Nevertheless, Jena kept its continued technological strengths in Optics and Instruments. Both technologies were identified as BTs according to our bridging measures. Overall, the BC calculated on the Revealed Relatedness matrix has a stronger correlation with the number of patents than the BI calculated on a simple co-occurrence matrix. Since the BC measure has a stronger theoretical foundation and seemed to better describe the Jena KS, we used it for subsequent, cross-regional and technology analyses.

For inter-regional comparisons, we introduce the Revealed Bridging Advantage (RBA) as a new index that captures regional specific technological strengths in bridging. This permits us to create comparisons both on a regional and on a technological level on the whole German KS. The results on the regional level show how some regions are more dynamic, so they are capable to increase their number of bridging advantages while others are more stable. In particular, we observe regions with historically high patenting activity like Stuttgart, Munich and Nuremberg are less dynamic than several smaller regions, such as Reutlingen, Karlsruhe, Soest, Wuerzburg, Dresden, and Augsburg able to introduce new bridging advantages at a higher than expected rate.

Regarding the technological level, we compare the embeddedness in the national KS and the regional diffusion. This analysis gives important insights about the positioning of single technologies in the German KS to understand if a technology is pervasive or localized or both. Our results show that there are three notable trends in the German KS. A first group of technologies becomes both less diffused and less embedded (*Transport*, *Other special machines* and *Chemical engineering*). In a second group there are technologies that become more diffused but less embedded (*Electrical machinery, apparatus, energy* and *Control*). The last group involves technologies that are both more diffused and more embedded (*Semiconductors*, *Computer technology*, *Measurement* and *Medical technology*). Our results indicate that the process of increasing embeddedness is not driven by single regions but rather a geographically dispersed phenomenon.

Applying similar methodologies on a single regional KS our results show that Jena has a relatively stable KS with few new bridging technologies compared to the other German regions. An analysis of single technologies in Jena suggests that new technologies that became important by the end of the period are mostly related to ICT. Others, such as *Biotechnology* or fields related to the pharmaceutical industry are loosing their importance in the Jena KS.

While our findings reveal the applicability of our proposed indices, our approach has several limitations. First,by using patents as the basis of the analysis, we can only identify patentable technologies. Thereby we neglect or at least underestimate important developments in fields such as services, software or business models. Second, since our approach relies on patent and technology classifications, we assume a sufficient amount of homogeneity within the respective classes and a similar homogeneity across classes. While this is already a strong assumption, the indices might be even more biased when technological classes are aggregated. Third, by focusing on co-occurrences, we do not observe directions of technological impact but rather cross-fertilization potentials. Finally, the relevance of bridging for the performance of regional economies as well as the factors driving it, such as its relation to inventor networks, need to be shown in subsequent research.

In addition, future research could try to identify the patents that establish these important links between different technologies and see if they have particular features in terms of quality measures or inventor and applicant characteristics. With existing quality measures (Squicciarini et al., 2013), it would be possible to understand if these patents are more valuable in terms of, for example, citations and if they spur the innovative activity of the area. Giving the ongoing discussion about the role of public research for technology development (Graf & Henning, 2009;

Graf & Menter, 2020) it could be a fruitful avenue to explore if public research is also a relevant actor in bridging technologies.

8 Acknowledgements

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A Betweenness based on co-occurrences

In this appendix we present our results for Betweenness Centrality if we use the simple Co-occurrence matrix instead of Revealed Relatedness. Overall, the results are quite similar despite some small differences in the technology rankings.

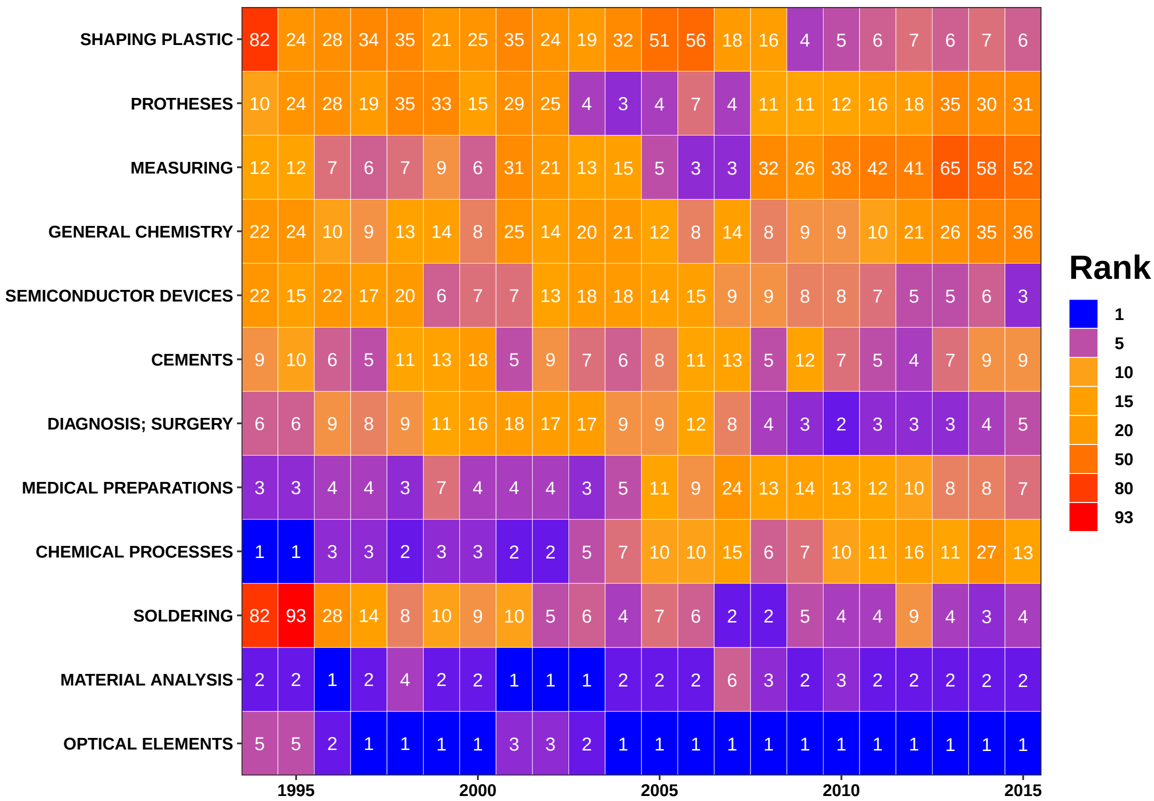

Figure 10: Node Betweenness Centrality on Co-occurrence matrix ranking in Jena (1990-2015)

B Descriptive statistics and correlations for all German regions

Table 2: Descriptive Statistics and Correlations in Germany

	Statistics							
	Descriptive Statistics					Correlations		
	Mean	SD	Minimum	Maximum	N	Brdg Ind	Bet Cent	Pat
Bridging Index	0.019	0.058	0	3.207	592669	1.00	\	\
Betweenness Centrality	271.406	672.264	0	14312.000	658156	0.56	1.00	\
Patents	9.009	25.559	1	1218.000	658156	0.45	0.52	1

C Schmoch Classification

The work of Schmoch (2008) on the classification of industrial activities is based on the IPC classification. To make it suitable for the CPC classification, it is necessary to make some assumptions. First, we created a new technological class denoted *Miscellaneous* in which all CPC 4 digit classes not present in the IPC classification are subsumed. These are mainly the ones of the Y class. Considering CPCs at a lower level than 4 digits, it is possible to identify some classes that are present in some different technological classifications. In this case, we opted to select the Schmoch technological field that is more represented (has the highest number of patents) in that specific CPC 4 digit class. A61K is mostly in field 16 *Pharmaceuticals*, but A61K-008 is in 14 *Organic fine chemistry*, H04N is mainly in class 2 *Audio-visual technology*, but also in 3 *Telecommunications* and 4 *Digital communication*, G01N is mainly in 10 *Measurement* but also with G01N-033 in 11 *Analysis of biological materials*, finally B01D is both in 23 *Chemical engineering* and 24 *Environmental technology*. We decided to keep all CPC 4 digit classes in one technological field, the one that worldwide had the highest presence of patents. So, A61K was assigned to *Pharmaceuticals*, H04N to *Audio-visual technology*, G01N to *Measurement* and B01D to *Chemical engineering*. Another factor to take into consideration is that the 4 digit CPC class is also identified in IPC but the correspondence at a lower level of classification (6 or 10 digits) tends to differ. In these cases, we assume that CPC 4 digit is exactly the same as IPC 4 digit to simplify calculations. Since the intention is to have some indications on the dominant technologies and the evolution of them the slight differences when passing from IPC to CPC are not taken into account.

Table 3: Schmoch Classification

Nr	Schmoch Technological Field	CPC Classes
0	Miscellaneous	A23V, Y02P, Y02T, Y02W, F05B, Y02E, Y02B, Y02C, F05D, D10B, C01P, C12Y, Y04S, E05Y
1	Electrical machinery, apparatus, energy	F21H, F21K, F21L, F21S, F21V, F21W, F21Y, H01B, H01C, H01F, H01G, H01H, H01J, H01K, H01M, H01R, H01T, H02B, H02G, H02H, H02J, H02K, H02M, H02N, H02P, H02S, H05B, H05C, H05F, H99Z
2	Audio-visual technology	G09F, G09G, G11B, H04N, H04R, H04S, H05K
3	Telecommunications	G08C, H01P, H01Q, H04B, H04H, H04J, H04K, H04M, H04Q
4	Digital communication	H04L, H04W
5	Basic communication processes	H03B, H03C, H03D, H03F, H03G, H03H, H03J, H03K, H03L, H03M
6	Computer technology	G06C, G06D, G06E, G06F, G06G, G06J, G06K, G06M, G06N, G06T, G10L, G11C
7	IT methods for management	G06Q
8	Semiconductors	H01L
9	Optics	G02B, G02C, G02F, G03B, G03C, G03D, G03F, G03G, G03H, H01S
10	Measurement	G01B, G01C, G01D, G01F, G01G, G01H, G01J, G01K, G01L, G01M, G01N, G01P, G01Q, G01R, G01S, G01V, G01W, G04B, G04C, G04D, G04F, G04G, G04R, G12B, G99Z
12	Control	G05B, G05D, G05F, G07B, G07C, G07D, G07F, G07G, G08B, G08G, G09B, G09C, G09D
13	Medical technology	A61B, A61C, A61D, A61F, A61G, A61H, A61J, A61L, A61M, A61N, H05G, G16H
14	Organic fine chemistry	A61Q, C07B, C07C, C07D, C07F, C07H, C07J, C40B
15	Biotechnology	C07G, C07K, C12M, C12N, C12P, C12Q, C12R, C12S
16	Pharmaceuticals	A61K, A61P
17	Macromolecular chemistry, polymers	C08B, C08C, C08F, C08G, C08H, C08K, C08L
18	Food chemistry	A01H, A21D, A23B, A23C, A23D, A23F, A23G, A23J, A23K, A23L, C12C, C12F, C12G, C12H, C12J, C13B, C13D, C13F, C13J, C13K
19	Basic materials chemistry	A01N, A01P, C05B, C05C, C05D, C05F, C05G, C06B, C06C, C06D, C06F, C09B, C09C, C09D, C09F, C09G, C09H, C09J, C09K, C10B, C10C, C10F, C10G, C10H, C10J, C10K, C10L, C10M, C10N, C11B, C11C, C11D, C99Z
20	Materials, metallurgy	B22C, B22D, B22F, C01B, C01C, C01D, C01F, C01G, C03C, C04B, C21B, C21C, C21D, C22B, C22C, C22F
21	Surface technology, coating	B05C, B05D, B32B, C23C, C23D, C23F, C23G, C25B, C25C, C25D, C25F, C30B
22	Micro-structural and nano-technology	B81B, B81C, B82B, B82Y
23	Chemical engineering	B01B, B01D, B01F, B01J, B01L, B02C, B03B, B03C, B03D, B04B, B04C, B05B, B06B, B07B, B07C, B08B, C14C, D06B, D06C, D06L, F25J, F26B, H05H
24	Environmental technology	A62C, B09B, B09C, B65F, C02F, F01N, F23G, F23J, G01T
25	Handling	B25J, B65B, B65C, B65D, B65G, B65H, B66B, B66C, B66D, B66F, B67B, B67C, B67D
26	Machine tools	A62D, B21B, B21C, B21D, B21F, B21G, B21H, B21J, B21K, B21L, B23B, B23C, B23D, B23F, B23G, B23H, B23K, B23P, B23Q, B24B, B24C, B24D, B25B, B25C, B25D, B25F, B25G, B25H, B26B, B26D, B26F, B27B, B27C, B27D, B27F, B27G, B27H, B27J, B27K, B27L, B27M, B27N, B30B
27	Engines, pumps, turbines	F01B, F01C, F01D, F01K, F01L, F01M, F01P, F02B, F02C, F02D, F02F, F02G, F02K, F02M, F02N, F02P, F03B, F03C, F03D, F03G, F03H, F04B, F04C, F04D, F04F, F23R, F99Z, G21B, G21C, G21D, G21F, G21G, G21H, G21J, G21K
28	Textile and paper machines	A41H, A43D, A46D, B31B, B31C, B31D, B31F, B41B, B41C, B41D, B41F, B41G, B41J, B41K, B41L, B41M, B41N, C14B, D01B, D01C, D01D, D01F, D01G, D01H, D02G, D02H, D02J, D03C, D03D, D03J, D04B, D04C, D04G, D04H, D05B, D05C, D06G, D06H, D06J, D06M, D06P, D06Q, D21B, D21C, D21D, D21F, D21G, D21H, D21J, D99Z
29	Other special machines	A01B, A01C, A01D, A01F, A01G, A01J, A01K, A01L, A01M, A21B, A21C, A22B, A22C, A23N, A23P, B02B, B28B, B28C, B28D, B29B, B29C, B29D, B29K, B29L, B33Y, B99Z, C03B, C08J, C12L, C13C, C13G, C13H, F41A, F41B, F41C, F41F, F41G, F41H, F41J, F42B, F42C, F42D
30	Thermal processes and apparatus	F22B, F22D, F22G, F23B, F23C, F23D, F23H, F23K, F23L, F23M, F23N, F23Q, F24B, F24C, F24D, F24F, F24H, F24J, F24S, F24T, F24V, F25B, F25C, F27B, F27D, F28B, F28C, F28D, F28F, F28G
31	Mechanical elements	F15B, F15C, F15D, F16B, F16C, F16D, F16F, F16G, F16H, F16J, F16K, F16L, F16M, F16N, F16P, F16S, F16T, F17B, F17C, F17D, G05G
32	Transport	B60B, B60C, B60D, B60F, B60G, B60H, B60J, B60K, B60L, B60M, B60N, B60P, B60Q, B60R, B60S, B60T, B60V, B60W, B61B, B61C, B61D, B61F, B61G, B61H, B61J, B61K, B61L, B62B, B62C, B62D, B62H, B62J, B62K, B62L, B62M, B63B, B63C, B63G, B63H, B63J, B64B, B64C, B64D, B64F, B64G
33	Furniture, games	A47B, A47C, A47D, A47F, A47G, A47H, A47J, A47K, A47L, A63B, A63C, A63D, A63F, A63G, A63H, A63J, A63K
34	Other consumer goods	A24B, A24C, A24D, A24F, A41B, A41C, A41D, A41F, A41G, A42B, A42C, A43B, A43C, A44B, A44C, A45B, A45C, A45D, A45F, A46B, A62B, A99Z, B42B, B42C, B42D, B42F, B43K, B43L, B43M, B44B, B44C, B44D, B44F, B68B, B68C, B68F, B68G, D04D, D06F, D06N, D07B, F25D, G10B, G10C, G10D, G10F, G10G, G10H, G10K
35	Civil engineering	E01B, E01C, E01D, E01F, E01H, E02B, E02C, E02D, E02F, E03B, E03C, E03D, E03F, E04B, E04C, E04D, E04F, E04G, E04H, E05B, E05C, E05D, E05F, E05G, E06B, E06C, E21B, E21C, E21D, E21F, E99Z

D LMR Abbreviations

Table 4: Abbreviations for Labour Market Regions in Germany

Region Name	Region Code
Aachen	AC
Altenkirchen	AK
Altoetting	AÖ
Amberg	AM
Ansbach	AN
Aschaffenburg	AB
Augsburg	A
Bad Kreuznach	BK
Bamberg	BA
Bautzen	BZ
Bayreuth	BT
Berlin	B
Bielefeld	BI
Bochum	BO
Boeblingen	BB
Bonn	BN
Borken	BOR
Braunschweig	BS
Bremen	BRMN
Bremerhaven	BRMR
Celle	CE
Cham	CHA
Chemnitz	C
Coburg	CO
Darmstadt	DA
Deggendorf	DEG
Dessau Rosslau	DSR
Donau Ries	DNR
Dortmund	DO
Dresden	DD
Duesseldorf	D
Elbe Elster	EE
Emden	EMD
Emsland	EL
Erfurt	EF
Erlangen	ER
Essen	E
Flensburg	FL
Frankfurt Oder	FO
Frankfurt Am Main	FAM
Freiburg	FR
Fulda	FD
Giessen	GSS
Goeppingen	GP
Goettingen	GÖ
Goslar	GS
Hagen	HA
Halle	HAL
Hamburg	HMB
Hameln	HM
Hannover	H
Havelland	HVL
Heidelberg	HD
Heidenheim	HDH
Heilbronn	HN
Hoexter	HX
Hof	HO
Ingolstadt	IN
Jena	J
Kaiserslautern	KL
Karlsruhe	KA
Kassel	KS
Kempten	KE
Kiel	KI
Kleve	KLE
Koblenz	KO
Koeln	K
Konstanz	KN
Landau	LAN
Landshut	LA
Leipzig	L
Limburg Weilburg	LW
Loerrach	LÖ
Ludwigshafen	LU
Luebeck	LB
Magdeburg	MD
Mainz	MZ
Memmingen	MM
Minden	MI
Muenchen	M
Muenster	MS
Nuernberg	N
Oberhavel	OHV
Oldenburg	OL
Olpe	OE
Ortenaukreis	OR
Osnabrueck	OS
Passau	PA
Pforzheim	PF
Pirmasens	PS
Potsdam Mittelmark	PM
Ravensburg	RV
Regensburg	R
Reutlingen	RT
Rostock	ROS
Rottweil	RW
Saalfeld Rudolstadt	SR
Saarbruecken	SB
Schwaebisch Hall	SHA
Schweinfurt	SW
Siegen	SI
Sigmaringen	SIG
Soest	SO
Stade	STD
Stuttgart	S
Suhl	SHL
Teltow Flaeming	TF
Traunstein	TS
Trier	TR
Ulm	UL
Vechta	VEC
Waldeck Frankenberg	WF
Waldshut	WT
Weilheim Schongau	WS
Weissenburg Gunzenhausen	WG
Wolfsburg	WOB
Wuerzburg	WÜ
Wuppertal	W
Zollernalbkreis	Z

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