The evolution of knowledge spaces: innovation, indicators and drivers

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Thesis overview

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Deutsche Zusammenfassung

In dieser Dissertation wird untersucht, wie sich Wissensräume im Laufe der Zeit verändern und welche Faktoren ihre Entwicklung vorantreiben. Die Arbeit ist in sechs Kapitel gegliedert. Kapitel 1 führt in das Thema ein und bietet eine Literaturübersicht über die Entwicklung von Technologien und technologischen Räumen sowie kurze Zusammenfassungen der nachfolgenden Kapitel. Die Kapitel 2 bis 5 bilden den Kern der Dissertation und liefern die wichtigsten Ergebnisse unter Berücksichtigung verschiedener Aspekte zu den Faktoren, die den Prozess der Entwicklung von Technologieräumen beeinflussen. Kapitel 6 schließt die Dissertation mit den wichtigsten Ergebnissen und Beiträgen, politischen Implikationen und weiteren Forschungsmöglichkeiten ab. Zur Gewinnung der Ergebnisse wurden verschiedene empirische Methoden verwendet, die von dem Differenz-von-Differenzen-Ansatz über die quantitative Textanalyse bis hin zur Analyse sozialer Netzwerke reichen. Außerdem wurden als Hauptdatenquellen sowohl Patente als auch Veröffentlichungen verwendet.

Technologien werden in der Innovationsliteratur als eine Sammlung von kombinierten Komponenten betrachtet. Diese Komponenten werden in Form von Netzwerken dargestellt. Diese Netzwerke werden üblicherweise als Wissensräume oder technologische Räume bezeichnet. Die einzelnen Komponenten (*nodes*) sind die Teile des Wissens, während die Beziehungen (*edges*) ihre Kombinationen darstellen. Sowohl Technologien als auch Wissensräume folgen einem evolutionären Prozess und werden durch interne und externe Faktoren beeinflusst. Die Rolle dieser technologischen Räume und ihre Entwicklung sind jedoch Aspekte, die in der Literatur noch nicht ausreichend untersucht wurden. Es gibt Technologien mit besonderen Merkmalen, die es ihnen erlauben, in Wissensräumen eine zentrale Rolle zu spielen. Ein

Beispiel für diese herausragenden Technologien sind die *General Purpose Technologies* (GPTs). GPTs sind *durchdringend*; eine Eigenschaft, die es ihnen erlaubt mit vielen anderen Komponenten verbunden zu sein. Außerdem haben sie *innovative Komplementaritäten*, sodass sie sinngemäß in der Lage sind auch die innovativen Aktivitäten innerhalb der Komponenten zu beeinflussen, die mit ihnen verbunden sind. Daher sind diese Technologien in der Lage auch die Entwicklung von Wissensräumen zu beeinflussen, welche die Innovation auch in den anderen Komponenten vorantreiben. In dieser Arbeit werden Veränderungen der Einbettung wichtiger Technologien im Wissensraum untersucht, wodurch Implikatinen bezüglich der Motivationen für solche Prozesse abgeleitet werden.

Vor der Bereitstellung von Instrumenten zur Messung dieser Veränderungen und zur Analyse der Treiber, die für die Entwicklung von Wissensräumen verantwortlich sind, konzentriert sich die Arbeit auf die Kategorisierung von Innovationsaktivitäten. Tatsächlich haben verschiedene innovative Aktivitäten unterschiedliche Auswirkungen auf Unternehmen, Technologien und Märkte. Normalerweise basiert die Charakterisierung verschiedener innovativer Aktivitäten auf den Auswirkungen, die sie auf diese Dimensionen haben. Viele verschiedene Begriffe wurden entwickelt, um bestimmte Auswirkungen hervorzuheben, die von anderen nicht aufgegriffen wurden. Häufig werden diese Begriffe jedoch anschließend als Synonyme verwendet, was zu einer Verwechslung der verschiedenen Konzepte führt. Dies ist auch ein Problem für die zuvor erwähnten technologischen Entwicklungen. Es ist wichtig genau zu bestimmen,wann eine Innovation in der Lage ist,den Pfad zu durchbrechen und völlig neue Branchen zu schaffen. Daher sollte eine genaue Definition dieser Art von Innovation vorgelegt werden. Kapitel 2 der Dissertation befasst sich mit der Klassifizierung von Innovationsbegriffen und schlägt eine Unterscheidung zwischen den gebräuchlichsten Innovationskonzepten vor, nämlich *radikal*, *disruptiv*, *diskontinuierlich*, *durchbrechend*, *kontinuierlich* und *inkrementell*. Die Ergebnisse bestätigen, dass es einen klaren Gegensatz zwischen außergewöhnlichen und nicht außergewöhnlichen Innovationen gibt. Dieser Gegensatz ist bei den Merkmalen und Auswirkungen von Innovationsbezeichnungen deutlich, während er bei den Anforderungen weniger deutlich ist. Darüber hinaus haben wir Innovationsbegriffe nicht nur anhand der häufigsten Dimensionen unterschieden (nämlich: Neuheit und

Wirkung), sondern auch anhand ihrer Technologie-/Marktorientierung und ihrer positiven/negativen Auswirkungen.

Nachdem die Hauptmerkmale der verschiedenen Arten von Innovationen, die für den Wandel der technologischen Paradigmen und damit der technologischen Räume verantwortlich sind, analysiert wurden, liefert die Dissertation neu entwickelte Indikatoren zur Bewertung ihrer Entwicklung. In der Literatur fehlen spezifische Maße zur Bewertung der Entwicklung und der Auswirkungen von Technologien auf den strukturellen Zusammenhalt von Wissensräumen. Die meisten Indikatoren verwenden Zählungen von Wissensinputs und -outputs, um die Qualität des produzierten Wissens zu bewerten. Sie berücksichtigen jedoch nicht, dass Aktivitäten zur Rekombination von Wissen für die Produktion von Innovationen wichtig sind. In diesem Sinne werden in dieser Arbeit Maße aus der Sozialen Netzwerkanalyse herangezogen, um die Qualität der technologischen Interaktionen innerhalb des Wissensraums zu bewerten. Kapitel 3 befasst sich mit der Definition und Identifizierung von *Brückentechnologien*. Dies sind Technologien, die als wichtig für die Struktur und den Zusammenhalt regionaler Wissensräume angesehen werden, da sie mit vielen anderen Komponenten verbunden sind. Wir stellen Analyseinstrumente zur Verfügung, die von der Analyse sozialer Netzwerke inspiriert sind, um sie zu identifizieren, und wir wenden diese Indikatoren an, um zu zeigen, wie sich die Technologien im Laufe der Zeit entwickeln. Die hier dargestellten Indikatoren werden auch in den Kapiteln 4 und 5 für die empirische Analyse verwendet. Die deskriptive Analyse der deutschen Wissensräume zeigt, dass große Patentregionen nicht in der Lage sind, die meisten Brückentechnologien im Technologieraum zu verankern und dass die Abhängigkeit Deutschlands von wichtigen Technologien (Maschinen, Verkehr und Chemie) abgenommen hat. Diese Veränderungen sind eher auf einen regional verteilten Prozess als auf einzelne Regionen zurückzuführen.

Die Umgestaltung und Entwicklung von Technologieräumen wird auch von einigen Triebkräften beeinflusst. In der Literatur wird in der Regel die Verbundenheit als Schlüsselfaktor für den Erfolg von Technologien betrachtet. Eine Analyse der Faktoren, die diese Technologien vorantreiben, und der Prozesse, die die Struktur von Technologieräumen verändern können, steht jedoch noch aus. In dieser Dissertation liegt der Schwerpunkt auf zwei möglichen Triebkräften, die die Entwicklung von Technologieräumen beeinflussen könnten. Die erste externe regionale Triebkraft ist die Clusterpolitik und die zweite interne regionale Triebkraft ist die Fähigkeit von Organisationen zur Wissensrekombination.

Was die erste Triebkraft betrifft, so haben sich die Forscher in letzter Zeit auf die systemischen Auswirkungen konzentriert, die eine Clusterpolitik mit sich bringt, wenn sie in einer bestimmten Region eingeführt wird. Die meisten dieser Studien verwenden Messgrößen aus der Sozialen Netzwerkanalyse um zu untersuchen, wie sich die Beziehungsstruktur der regional verankerten Organisationen nach der Einführung einer Politik verändert. Im Allgemeinen stellen sie positive kurzfristige Auswirkungen fest. Die Zunahme der Kooperationsaktivitäten fördert jedoch die Möglichkeiten der gegenseitigen Befruchtung im technologischen Bereich. Dieser Effekt führt letztlich zu einer Neugestaltung der Struktur des Wissensraums. Kapitel 4 befasst sich mit den Auswirkungen, die eine Clusterpolitik auf den Technologieraum hat. Wir haben sowohl kurzfristige als auch langfristige Auswirkungen gemessen, indem wir die Entwicklung der Technologieräume vor, während und nach der Einführung einer Clusterpolitik analysiert haben. Die Neuheit der Studie besteht darin, dass das Konzept der Wissensräume unseres Wissens nach noch nie verwendet wurde, um die Auswirkungen einer solchen Politik zu verstehen. Wir wenden dies auf eine einzelne Clusterpolitik an, den deutschen BioRegio-Wettbewerb. Dabei handelt es sich um ein Programm, das entwickelt wurde, um die Zusammenarbeit auf dem Gebiet der Biotechnologie zu verstärken und sie mit anderen, nicht verwandten Technologien in ausgewählten Regionen zu kombinieren. Wir verfolgen die Entwicklung der Biotechnologie in allen Regionen, die an dem Wettbewerb teilgenommen haben, indem wir einen Differenz-von-Differenzen-Ansatz und die *Betweenness Centrality* als Maß für die Einbettung dieser Technologien in den Wissensraum verwenden. Die Ergebnisse zeigen, dass das Programm sowohl zur Steigerung der Bedeutung der Biotechnologie als auch zu einem gegenseitigen Befruchtungseffekt in den Regionen, die den Wettbewerb gewonnen haben, beigetragen hat.

Die zweite Triebkraft sind die regionalen Organisationen, in denen das Wissen auf einzigartige Weise kombiniert und neu kombiniert wird. Durch diese Tätigkeit sind einige Organisationen in der Lage, radikale Veränderungen herbeizuführen und so den technologischen Raum neu zu gestalten. Die

Faktoren, die ihre Neigung, Wissen anders als andere zu kombinieren, beeinflussen, sind unterschiedlich. In der Literatur fehlt jedoch eine Analyse, die diese Faktoren berücksichtigt und bewertet, welche Organisationen in der Lage sind, technologische Räume neu zu gestalten. Kapitel 5 befasst sich mit diesem letzten Ziel der Arbeit und erkennt die Faktoren, welche die Neigung von Organisationen beeinflussen, Wissen anders als andere zu kombinieren. Diese beiden Faktoren sind die Positionierung, die sie innerhalb des regionalen Innovationsnetzwerks einnehmen, und ihre Ausrichtung auf angewandte oder Grundlagenforschung. Um darzustellen, welche Organisationen Technologien anders als andere kombinieren, schlage ich einen neuen Indikator vor, der von der Analyse sozialer Netzwerke inspiriert ist und Redundanzkoeffizient heißt. Dieses Maß ist in der Lage, die von den Antragstellern kombinierten Technologien zu erfassen, die von keinem anderen Unternehmen im Wissensraum kombiniert werden. Die Ergebnisse zeigen, dass öffentliche Forschungsinstitute Wissen nur dann auf andere Weise kombinieren, wenn sie im regionalen Innovationsnetzwerk eine zentrale Rolle spielen. Private Institute hingegen sind in der Lage, Technologien auf andere Weise zu kombinieren, wenn sie zentral eingebettet sind, aber auch, wenn sie sich in der Peripherie des regionalen Innovationsnetzwerks befinden. Diese Ergebnisse deuten also darauf hin, dass sowohl die Ausrichtung auf angewandte oder Grundlagenforschung als auch die Einbettung in das regionale Innovationsnetzwerk für die Art und Weise, wie Technologien kombiniert werden, von Bedeutung sind. Politische Entscheidungsträger sollten öffentliche Forschungseinrichtungen dabei unterstützen, eine zentrale Position im regionalen Innovationsnetzwerk einzunehmen, die es ihnen ermöglicht, für den Wissensraum wichtige Technologien zu kombinieren und so eine solide Wissensbasis zu schaffen.

Zusammenfassend lässt sich sagen, dass die Dissertation einen Beitrag zur aktuellen Literatur leistet, indem sie verschiedene Erkenntnisse über die Triebkräfte liefert, die die Entwicklung von Technologieräumen bestimmen, und Instrumente zur Messung dieser Veränderungen bereitstellt. Diese beiden Aspekte sind in der Literatur oft nicht ausreichend erforscht. Ausgehend von diesem Beitrag können daher weitere Forschungsarbeiten aufzeigen, wie Veränderungen im Technologieraum die künftige Innovations- und Wirtschaftsleistung einer Region oder eines Landes beeinflussen können.

Chapter 1

Introduction

1.1 The evolution of knowledge spaces

In innovation studies, technologies are usually regarded as a *recipe* which includes a collection of combined components (Sorenson and Fleming, 2004; Dosi and Nelson, 2010). The components are the pieces of knowledge whereas the relations are their combinations (Fleming and Sorenson, 2001). Usually, the components and their relations are represented in the network form, frequently called knowledge spaces (Kogler, Rigby, and Tucker, 2013; Quatraro, 2010). This thesis is interested in providing tools to measure the importance of components inside knowledge spaces and to study the drivers that shape their development.

The components inside a knowledge space can be directly or indirectly related (Broekel, 2019). The "distances" between the nodes (components) represent their degree of relatedness. In the general formulation, two technologies are related if they share the same knowledge base, have similar technological content and their development requires similar skills (Nooteboom, 2000; Boschma and Iammarino, 2009). When two highly unrelated components are combined, the chance to develop an exceptional innovation increases (Ahuja and Lampert, 2001). This concept has been used by many researchers to quantify the importance of knowledge spillovers (Nelson and Winter, 1982; Sorenson and Fleming, 2004) and to explain how knowledge is produced in time and space (Boschma, Minondo, and Navarro, 2013; Boschma, 2017).

Particular technologies (and the knowledge that they contain) have particular characteristics, putting them in a central position inside knowledge spaces (Graf, 2012). Economists and scholars from other fields study the main features of technologies, identifying them as continuously evolving assets following an evolutionary process (Dosi, 1988; Dosi and Nelson, 2010). Normally, technical advances are achieved following a trajectory path within the limits of a "paradigm". General Purpose Technologies (GPTs) are one specific example of prominent technologies (Tushman and Anderson, 1986; Bresnahan, 1986). Their *pervasiveness* permits them to be connected to many other components (Rosenberg and Trajtenberg, 2004; Malerba and Orsenigo, 1997; Cantner and Vannuccini, 2017). Moreover, they have *innovational complementarities*, in the sense that when a General Purpose Technology is improved, this creates an incentive to ameliorate also the connected components (Cantner and Vannuccini, 2017). Therefore, technologies connected to many others are expected to occupy a central position in the knowledge space and to drive its evolution. In this thesis, through the study of the changes in embeddedness of particular technologies, I derive implications on the drivers involved in this process.

The first objective of the thesis is to characterize *innovation* activities. Innovation activities are the basic source of technological progress (non-exceptional innovations), and they are important for the generation of new paradigms (exceptional innovations). Both exceptional and non-exceptional innovations have different sources, different characteristics and different impacts on firms, on technologies and, ultimately, on markets. Therefore, it is important to distinguish them based on the previously mentioned factors. These innovative activities, for example, are able to change the way how technologies are combined inside the knowledge space.

In the literature so far, there is little understanding on how the structure of technological spaces evolve over time. It is unclear which are the technologies that occupy a central position in technological spaces, with similar characteristics as GPTs, acting as a base for the development of many other technologies. These important technologies could, once they have reached the maturity phase, lose their central position in favour of other (newer) technologies. Thus, the second objective of the thesis is to provide new *indicators* for measuring the evolution of technologies inside the regional technological space. Strictly connected to the second objective, the changes in the structure of technological spaces can be determined also by external or internal *drivers*. Using the developed indicators following the second objective of the thesis, I discern how external or internal drivers can influence the structure and thereby transform technological spaces. Even if I am not able to analyse all the mechanisms responsible for the evolution of technologies, the thesis contributes to the scarce literature regarding technological spaces and provides analytical tools for analysing their evolution.

In the following, the three objectives (namely: *innovation*, *indicators* and *drivers*) of the thesis are analysed on a detailed level.

1.1.1 Innovation categorization

Different innovations have different effects and characteristics. For example, the steam engine is considered a *radical* innovation because it created completely new markets and industries by destroying existing ones. Instead, the introduction of a new smartphone model every year is regarded as an *incremental* innovation because it only introduces improvements to the existing product without creating new industries or markets.

In the economics literature, novelties are distinguished based on their impact on technological change and growth. The most common distinction is between *non-exceptional* and *exceptional* innovations. *Exceptional* innovations represent something really new, able to create completely new industries and destroying existing supply and demand (Hill and Rothaermel, 2003; Büschgens, Bausch, and Balkin, 2013; Dewar and Dutton, 1986). *Non-exceptional* innovations are commonly described as small improvements, adjustments or further developments of a technology or a product already present in the industry or in the market (Arts, Appio, and Van Looy, 2013; Arts and Veugelers, 2015). The technological impact of these innovations is usually small (Dewar and Dutton, 1986; Henderson and Clark, 1990; Schoenmakers and Duysters, 2010).

This dichotomy can be easily translated into the theory of technological paradigms. Dosi (1982) distinguishes between changes continuously happening along already existing trajectories (*non-exceptional* innovations) and novelties able to challenge existing paradigms (*exceptional* innovations). In this sense, *non-exceptional* and *exceptional* innovations matter for technological evolution, and they could reshape evolutionary trajectories, depending on their innovative potential.

Scholars in innovation economics under the umbrella of *exceptional* and *non-exceptional* innovations have conceptualized many different terms to characterize innovation activities. Terms are introduced by authors to emphasize some characteristics that have not been touched upon by others. However, often these labels are used as synonyms, creating confusion among them (Garcia and Calantone, 2002). Therefore, when researchers and practitioners have to assess the impact of a specific innovation, they have difficulties learning from the scientific results if the terminology is too unclear (Garcia and Calantone, 2002). Moreover, the same innovation may be identified as both *exceptional* or *non-exceptional* depending on who analyses its impact (Linton, 2009). This is obviously a problem also for the aforementioned technological trajectories. Identifying when an innovation is able to break the path and create new industries is crucial, and finding a definition that suits this innovation in terms of its specific characteristics should be straightforward.

The first research objective is to differentiate innovations based on their intrinsic dimensions.

1.1.2 Indicators for measuring changes in Knowledge Spaces

One of the more accepted theories among scholars in innovation economics is that the production of knowledge and technological change is important for economic advances also at the regional level (Romer, 1986; Robert and Lucas, 1988; Scott, 2006). To measure the generation of knowledge in space and time, many scholars use the concept of knowledge relatedness (Alstott, Triulzi, Yan, and Luo, 2017; Boschma, 2015; Neffke, Henning, and Boschma, 2011; Boschma et al., 2013). Relatedness is frequently used to reconstruct the knowledge space, i.e. the network of interrelated technologies (structural elements with specific functions and properties), of a region or an economy (Kogler et al., 2013). This concept permits an understanding of which technological competences are locally present and how they influence innovative activity. The knowledge space is not static but rather changes over time and is, among others, affected by the emergence of prominent technologies. These technologies will hold a central position in the knowledge space affecting the improvement (in terms of new inventions) of the other technologies connected to them (Graf, 2012).

In the literature, Graf (2012), for example, uses measures from Social Network Analysis to identify such important technologies in knowledge spaces. However, specific indicators for measuring the evolution and impact of technologies on the structural cohesiveness of the knowledge space are rare. Many of the indicators used in innovation studies and related fields use counts of knowledge inputs and outputs to assess the quality of knowledge that has been produced (Balland and Rigby, 2017). For example, the mere count of patents present in a technology considers only its diffusion whereas such a measure does not consider the interrelations with other technologies. Moreover, forward and backward citations in patents consider only the direct links among technologies. However, they fail to account for the ramifications of the technological network on technologies around the focal technology. Thus, these measures do not take into account the fact that some technologies are more important than others for the structural cohesiveness of the knowledge space and that knowledge recombination activities are important for the production of novelties. In this sense, measures taken from Social Network Analysis better consider the quality of technological interactions within the knowledge space.

The second research objective is to provide new indicators for measuring the importance of technologies for the general cohesiveness and evolution of knowledge spaces.

1.1.3 Drivers reshaping the evolution of Knowledge Spaces

Knowledge spaces are not static they are influenced by changes in the local and global economy. For example, in a technological space where a specific technology is well-embedded, a crisis in this and related fields would lead the exploration of new technological avenues within the knowledge space. Existing research provides only limited findings on how different drivers can reshape the technological evolution of nations and regions. An analysis on the factors able to drive these technologies and which processes are able to change the structure of technological spaces as a whole are still largely unknown (Boschma, 2017). Every *driver* needs a specific approach in order to study its effects on the structure of knowledge spaces. This is the motivation behind my focus mainly on two in this thesis. The first external regional driver presented in this thesis is cluster policies, and the second internal regional driver is the regional organizations (intended as the actors where technological components are combined).

The main aim of a cluster policy is to create collaboration activities among actors present locally. Therefore, when actors active in different technologies create a connection for the first time, this creates also a link in the technological space. If this is the case, this collaboration is repeated, and the effects on the structure of the technological space are huge. Recent literature assesses the impact of cluster policies on the structure of relationships of regionally-embedded organizations, providing evidence for positive effects of cluster policies on network cohesion (Giuliani, Matta, and Pietrobelli, 2016; Töpfer, Cantner, and Graf, 2019; Graf and Broekel, 2020; N'Ghauran and Autant-Bernard, 2020). The increased collaboration among actors present locally increases the number of innovative activities and, ultimately, the possibilities for cross-fertilization opportunities between organizations specialized in different technologies (Eickelpasch and Fritsch, 2005). Since cluster policies are targeting specific technologies, these can possibly change their embeddeddness in the technological space. This effect is able to reshape the evolutionary trajectories of technological spaces, an aspect that has been not yet analysed in literature.

The micro-units where knowledge is combined and re-combined in a unique way are the organizations present locally (Boschma, 2017; Fornahl, Broekel, and Boschma, 2011). Some of these organizations are responsible for the development of radical changes, and thus they are able to reshape the technological space (Tanner, 2014; Gilbert and Campbell, 2015). The attitude of these organizations to combine in a unique way knowledge is influenced by two factors. As already defined by Miller, Miller, and Dismukes (2005), Graf (2017), Graf and Menter (2021) the factors are: their propensity towards basic or applied research and their embeddedness in the regional innovation network. However, an analysis that considers these factors and assesses which are the organizations potentially able to reshape technology spaces is missing in the literature (Boschma, 2017).

The third research objective is to assess the impact of external and internal drivers on technological trajectories in knowledge spaces.

1.2 Structure of the thesis

The thesis is composed of four papers identified as Chapters 2-5. Chapter 2 is intended to disentangle differences and similarities of different innovation labels. Chapter 3 is focused on providing new indicators for measuring the evolution of knowledge spaces. Chapters 4 and 5 are focused on the drivers able to reshape the development of knowledge spaces (respectively policy intervention and the role of organizations). Table 1.1 offers a summary of the key aspects of each Chapter.

1.2.1 Chapter 2

The second Chapter, "Revisiting innovation typology: A systemic approach", aims to classify and distinguish among the different innovation labels. Different terms are used interchangeably in the literature due to partial overlap in their characteristics. Innovation labels present challenges when they are used in empirical studies. This is particularly true when theoretical definitions are operationalised.

There are various types of innovations defined in the literature. For example, exceptional innovations are called *radical*, *discontinuous*, *disruptive* or *breakthrough* (Kovacs, Marullo, Verhoeven, and Van Looy, 2019) while non-exceptional innovations are labeled as *incremental* or *continuous*. Recently, the label *radical* has become the concept that most of all characterises exceptional innovations (Kovacs et al., 2019). Even if the use of this label is

Table 1.1: Thesis overview.

	Chapter 2	Chapter 3	Chapter 4	Chapter 5
Title	Revisiting innovation typology: A systemic approach	Bridging Technologies in the Regional Knowledge Space: Measurement and Evolution	Policy Influence in the Knowledge Space: a Regional Application	The influence of organizations on technological combinations: an application on German regions
Co-authors	Louis Knüpling and Colin Weßendorf	Holger Graf	Uwe Cantner and Holger Graf	-
Theoretical foundation/Field	Innovation definitions and terminology	Technological evolution, New Measures, General Purpose Technologies, Key Enabling Technologies	Policy evaluation, Knowledge Space, Technological Embededdness	Institutions, knowledge formation and recombination
Dimension	Innovation	Indicators	Drivers: Cluster Policy	Drivers: Organizations
Methodology	Quantitative text analysis	Social Network Analysis (SNA), Relatedness	SNA, Difference-in-Difference regression, Relatedness	SNA, Fixed Effect
New measures introduced/Novel approaches	Systematic literature review to distinguish among different innovation terms	Bridging Index (BI), Revealed Bridging Advantage (RBA)	Betweenness Centrality as a tool to identify the evolution of prominent technologies	Redundancy Coefficient (RC)
Spatial coverage	-	German Labour Market Regions, world (only for the construction of the relatedness matrix)	German Labour Market Regions participating to BioRegio program, world (only for the construction of the relatedness matrix)	German Labour Market Regions
Observation Period	-	1990-2015	1986-2014	2010-2015
Data	Publication data	PATSTAT, Schmoch classification of technologies, Cooperative Patent Classification (CPC)	PATSTAT, OECD classification of technologies, International Patent Classification (IPC)	PATSTAT, Cooperative Patent Classification (CPC), HAN classification of applicants
Own Contribution	Significant contribution to the design of the study, data collection, theoretical and empirical elaborations, and interpretation of the results	Significant contribution to the design of the study, data collection, theoretical and empirical elaborations, and interpretation of the results	Significant contribution to the design of the study, data collection, theoretical and empirical elaborations, and interpretation of the results	-
Status	In preparation for submission. Available as working paper in JERP: No. 2022-002	Submitted to the Journal of Evolutionary Economics. Available as working paper in JERP: No. 2020-012	Published in the Journal of Technology Transfer. DOI: 10.1007/s10961-022-09925-1	In preparation for submission.

widespread, it lacks of a clear distinction with other similar concepts (Audretsch, Fornahl, and Klarl, 2022; Gopalakrishnan and Damanpour, 1997). This leads to inconsistencies and ambiguities about the discrimination of the different innovation labels. For example, other authors like Garcia and Calantone (2002), Gatignon, Tushman, Smith, and Anderson (2002), Linton (2009), Kovacs et al. (2019) have already addressed the issue of interchangeable use of innovation labels. One way to distinguish the innovation labels is through their degree of novelty; however this characterization is often inconsistent (Garcia and Calantone, 2002). The same innovation can be identified as *radical* from one author or firm and *incremental* from another one (Garcia and Calantone, 2002; Linton, 2009). Multiple challenges arise from these inconsistencies. First, research that uses different labels may be neglected by practitioners during the research process. Second, old findings can be simply refreshed by using new terminology without providing something really new. Third, for practitioners it is difficult to learn from the results if the terminology is not clear (Garcia and Calantone, 2002).

The objective of this Chapter is to find unique features of the innovation terms that would permit their distinction from the other labels. This research can allow scholars to reach clearer research results, pushing the creation of knowledge in the field of innovation studies further. To operationalise this, firstly, we examine which are the features of the single innovation terms. Secondly, we assess how these labels differ from one to the other based on their requirements (input), features (content) and effects (output).

Methodologically, in order answer these research questions we retrieve more than 500 scientific papers from the Web of Science that contain one of the aforementioned labels. We assign manually the features to each innovation term, and we quantitatively assess the characteristics. With the definition of the requirements, features and effects for each innovation label, we contribute to develop a better understanding of the differences and commonalities of each term.

The results confirm the clear opposition between the exceptional and ordinary innovations. This result is clear on the side of the features and effects whereas it is less clear on the side of the requirements. Furthermore, other than the classical dimensions of novelty and impact, we find two other aspects (technology vs. market orientation and positive vs. negative effects) important for differentiating further among single innovation labels. In our results *breakthrough*, innovation has a clear technology and knowledge association. Therefore, it refers more to the technical invention rather than marketed products whereas *disruptive* and *radical* are clearly related to the market and product side. Moreover, *incremental* and *breakthrough* are usually associated with positive effects but *disruptive* and *discontinuous* are more related to negative effects.

This Chapter is co-authored with Louis Knuepling and Colin Wessendorf. I contributed significantly to the design of the study, the data collection, the theoretical and empirical elaborations as well to the interpretation of the results. The Chapter has been published as working paper in Jena Economic Research Paper (JERP) series: No. 2022-002.

1.2.2 Chapter 3

The third Chapter, "Bridging Technologies in the Regional Knowledge Space: Measurement and Evolution", focuses on the definition of Bridging Technologies (BTs), their identification and their evolution over time. The BT concept indicate technologies important for the knowledge base of regions capable of connecting different fields which enable technological development. Using measures widely diffused in Social Network Analysis (SNA), this Chapter provides reproducible tools for BTs identification and for measuring their evolution over time. These methods are used in subsequent chapters of the thesis to assess the impact of *drivers* on the evolution of technological spaces.

Schumpeter (1939) identify innovation and growth cycles as processes initiated by the development of prominent technologies. Dosi (1982) used the term "technological paradigms" to discuss the emergence of new technologies able to substitute previous, mature ones. This study initiated a strand of literature whose main aim is to show the characteristics of these paradigms. These studies contributed to the definition of General Purpose Technologies (GPTs). These technologies are able to drive progress and growth in a region, a nation or worldwide (Bresnahan and Trajtenberg, 1995). An "evolution" of GPTs is the definition of Key Enabling Technologies (KETs). KETs are a subset of GPTs, and these technologies have the particular characteristic of *enabling* subsequent advances, which in turn lead to greater chances for technical advances (Bresnahan and Trajtenberg, 1995). Based on these two concepts (GPTs and KETs) we define the term Bridging Technology (BT). This is a particular type of technology able to link other fields of knowledge that, without this specific connection, would result distant in the regional knowledge space. This function affects the cohesiveness of the regional knowledge space (Quatraro, 2010), and it is derived from the concept of "pervasiveness" of GPTs and KETs.

For identifying BTs, we propose two alternative concepts based on the centrality of a technology in the technological space. Moreover, we provide analytical tools inspired from SNA to identify them. We apply these indicators to show the development of technologies over time. For a regional comparison, we propose a new index called Revealed Bridging Advantage (RBA), a specialization index inspired by the Balassa indicator. Therefore, we contribute to the BTs literature and to the general understanding on how these are formed inside the technological spaces.

This Chapter is mainly methodological, and the main aim is to provide tools and insights that will be used in subsequent chapters to identify determinants responsible for pursuing specific technological trajectories on the regional level. The descriptive analysis of the German regional knowledge base shows that large patenting regions are not the ones able to embed most BTs in the technological space and that Germany became less dependent on important technologies (machinery, transport and chemicals). These changes are driven by a regional dispersed process rather than by single regions.

The indexes developed in this Chapter are used and adapted in Chapters 4 and 5. This Chapter is co-authored with Holger Graf. I contributed significantly to the design of the study, the data collection, the theoretical and empirical elaboration as well to the interpretation of the results. The Chapter has been submitted to the Journal of Evolutionary Economics and it has been already published as a working paper in Jena Economic Research Paper (JERP) series: No. 2020-012. In the following chapters is referred to as Basilico and Graf (2020).

1.2.3 Chapter 4

The fourth Chapter, "Policy Influence in the Knowledge Space: a Regional Application", aims to understand how regional knowledge spaces respond to the introduction of a cluster policy. Recent cluster policy evaluation studies analysed how the actor-based knowledge network are affected by these measures. We continue in this direction by examining how the technological spaces evolved before, during and after the introduction of such policies. We are mainly interested in long-term structural effects usually not accounted for in other policy evaluation studies.

The main aim of cluster policies is to improve collaboration between actors that are located in the same area to target systemic failures. However, evaluation studies are mainly focused on the effects visible at the firm level (Nishimura and Okamuro, 2011). Since the goals of this policy instrument are manifold and require complex interactions, many scholars call for assessments that take into account the systemic nature of these measures (Mar and Massard, 2021; Rothgang, Lageman, and Scholz, 2021). There are few recent studies tackling these deficiencies, and they use methods from Social Network Analysis (SNA) to understand how policy affects the structure of relationships between different actors providing limited evidence for positive effects on network cohesion (Giuliani et al., 2016; Töpfer et al., 2019; Graf and Broekel, 2020; N'Ghauran and Autant-Bernard, 2020).

One of the determinants that influences economic growth on the regional level is the knowledge space (Kogler et al., 2013; Hidalgo, Klinger, Barabasi, and Hausmann, 2007; Hausmann and Klinger, 2007). Taking into consideration that innovation-oriented cluster policies are targeted to hit a specific technology, we presume that such policies are able to reshape the knowledge space of regions. The novelty of the study resides here, as the concept of knowledge spaces has never been used to understand the effects of such policies, to our knowledge. These innovation-oriented cluster policies stimulate various collaborative activities in some industries or technological fields. Therefore, the supported fields should become more visible in the knowledge space either by enhancing the number of links within the industry or by the creation of links with other fields (cross-fertilization).

To test if cluster policies are able to reshape knowledge spaces, we focus on the German BioRegio Contest. This was a specific program developed by the German federal government to foster collaborations among biotechnological start-ups and to combine biotechnology with other related or unrelated technologies (Dohse, 2000; Dohse and Staehler, 2008). The combination and recombination activities are particularly important for our study since cross-fertilization effects could reshape the knowledge space of the regions involved.

We track the evolution of biotechnology in all regions that participated to the contest using a Difference-in-Differences (DiD) approach and betweenness centrality as a measure of embeddedness of technologies in the knowledge space. The results show that the program contributed both to an increase of the importance of biotech and to a cross-fertilization effect in the regions that won the contest. Furthermore, we find that biotech in the winning regions experienced a higher growth than biotech in the non-winning regions after the funding for the program ceased.

This Chapter is co-authored with Uwe Cantner and Holger Graf. I contributed significantly to the design of the study, the data collection, the theoretical and empirical elaborations as well to the interpretation of the results. The Chapter has been published in the Journal of Technology Transfer, DOI: 10.1007/s10961-022-09925-1. In Chapter 5 is regarded as Basilico, Cantner, and Graf (2022).

1.2.4 Chapter 5

The fifth and final Chapter, "The influence of organizations on technological combinations: an application on German regions", aims to understand which categories of organizations in the Regional Innovation Network (RIN) are able to combine prominent technologies important for the regional technological spaces.

Regionally embedded agents are the units where knowledge is combined to create innovative activities. A perspective on the actors responsible to combine technologies important for regional development is missing in the literature (Boschma, 2017). I recognize two forces able to influence the ability of agents to combine technological elements important for regional development. The first element is the position that they occupy inside the regional innovation network (Boschma, 2017), and the second is their orientation towards basic or applied research (Graf and Menter, 2021; Graf and Henning, 2009). Agents considered important are the ones able to combine technologies in a different way with respect to others. They can drive the region to explore new technological trajectories, introducing new technologies in the knowledge space (Tanner, 2014; Gilbert and Campbell, 2015).

To understand which are the agents that combine technologies in a different way than others, I propose a new indicator inspired from Social Network Analysis called the Redundancy Coefficient (RC) (Latapy, Magnien, and Del Vecchio, 2008). This indicator measures how applicants combine technologies that no one else is combining in the knowledge space. In order to identify these important actors, I run a series of regressions where my unit of observation is the single organization. The main independent variables are a series of dummies to assign the applicant to a specific research category (to assess if the nature of the research of the agent is more towards applied or basic) and an indicator (degree centrality) able to identify the centrality of an applicant in the regional innovation network.

Results show that more basic research institutes are combining technologies not combined by other organizations present in the region only when they occupy a central position in the regional innovation network. By contrast, private institutes are able to combine technologies in a different way both when they are central and when they are in the periphery. Thus, the orientation towards more applied or basic research as well as the embededdness in the regional innovation network matter for the propensity to combine knowledge in a different way than others. Therefore, the policy implications of this Chapter relate to the fact that policy makers should support public research institutes by increasing collaboration and transfer activities with private organizations. If this is the case, public institutes would have access to a varied asset of knowledge. Therefore they would hold a central position in the regional innovation network. When they do so, these organizations are able to combine technologies in a different way, enabling the possibility to produce radical innovations (Graf and Menter, 2021). These results suggests that public institutes should leave their ivory tower culture to occupy a more central role in the regional innovation network (Etzkowitz, Webster, Gebhardt, and Terra, 2000). This would help them to combine technologies important for the survival of the knowledge space, creating a solid knowledge base that through spillovers could flow to other entities.

This Chapter is single-authored and currently is under preparation for submission in a scientific journal.

Chapter 2

Revisiting innovation typology: A systemic approach

2.1 Introduction

Innovations are differentiated into various types. Rather exceptional innovations, are often labelled *radical*, *discontinuous*, *disruptive* or *breakthrough* (Kovacs et al., 2019), whereas more ordinary innovations are labelled *incremental* or *continuous*. Between 1999 and 2015, radical innovation evolved as the most important concept that characterizes exceptional innovations (Kovacs et al., 2019). Despite its popularity, it lacks a coherent distinction from other important innovation concepts (Audretsch et al., 2022; Gopalakrishnan and Damanpour, 1997). For example, Kovacs et al. (2019) demonstrate that more than two thirds of the authors covering innovation-related topics use several labels in different publications, which they explain with a highly related 'intellectual origin' (p. 23). Innovations are often categorized based on their novelty, but the categories are inconsistent (Garcia and Calantone, 2002). One firm or one author may identify an innovation as *radical*, while other firms or authors would refer to the same innovation as *incremental* (Garcia and Calantone, 2002; Linton, 2009). As Gopalakrishnan and Damanpour (1997) point out, even the label *innovation* itself is interpreted differently from different perspectives and by different scholars. The resulting confusion bears multiple challenges: First, relevant literature which uses a different terminology may be overlooked in the research process. Second, at the same time, old findings can be simply refreshed with a new terminology instead of really bringing forward something new. Third, practitioners can hardly learn from scientific results if the terminology is too unclear (Garcia and Calantone, 2002).

Previous studies address the terminological problems in different ways. Gatignon et al. (2002) put forward a structural approach to innovation assessment into its locus, the type, and characteristics. Garcia and Calantone (2002) argue for a distinction into micro- and macro-level effects and between effects on technology and marketing. Linton (2009) calls for the consideration of innovation inputs, outputs, and the perspective (different perception of innovations depending on the firm). All these approaches can help to classify single innovations more precisely compared to labeling them as *radical* or *disruptive*. However, innovation labels are widely used, because they combine several underlying characteristics, which helps in classifying innovations in large-scale empirical studies and to compare empirical results. Though, it requires a delineation of the different innovation labels in order to assure the underlying characteristics are clear. In this regard, only Kovacs et al. (2019) systematically review the origin and scientific usage of *radical*, *disruptive*, *discontinuous*, and *breakthrough* as the most common labels for exceptional innovations. Their analysis of definitions in 100 highly cited papers allows for a differentiation between on the one hand *radical* and *discontinuous* (as novel innovations) and on the other hand *disruptive* and *breakthrough* as impactful innovations. Though, it does not allow for any further discrimination.

Therefore, the objective of this chapter is to systematically assess the characteristics associated with different innovation labels in the literature on a larger scale (over 500 articles), in order to come up with a set of distinctive properties. This categorization can enable clearer operationalization in empirical research, thus pushing knowledge creation in the field of innovation research further and rendering the applicability of scientific results easier for practitioners. Inspired by the studies of Gatignon et al. (2002) and Linton (2009) we collect innovation characteristics from definitions in scientific articles in a systemic way from requirements (input) to descriptive features (content), and effects (output), as also suggested by Audretsch et al. (2022). Differently from other studies, we do not limit ourselves to a basic distinction of the main requirements, features and effects. We provide a more in-depth analysis to better characterize the different innovation labels. Practitioners and other researchers, when faced with choosing the right label for their study, can be guided by the findings of our research, thus reducing ambiguity.

In the first step, we inductively code the characteristics assigned to different innovation labels in more than 500 scientific papers retrieved from the Web of Science. Then, we aggregate the codes to broader dimensions, allowing as to quantitatively assess the most decisive characteristics for a coherent distinction. In determining the core requirements, features, and effects associated with each innovation label, we develop a better understanding of their differences and commonalities. In order to detect also shared characteristics between all 'exceptional' innovations, we add *incremental* and *continuous* as labels for rather ordinary innovations to the four labels analyzed by Kovacs et al. (2019).

Our set of dimensions allows a clear differentiation between exceptional (more novel and more impactful) and ordinary innovations (less novel and less impactful). Innovation requirements, however, vary to a lesser extent between the labels, which highlights that the necessary conditions and inputs for innovation do not predict innovation outcomes as good as expected by previous studies (Kovacs et al., 2019). Moreover, beyond refining the positioning of labels within the dimensions of novelty and impact, we highlight two further dimensions (technology vs. market orientation and positive vs. negative effects) that help to differentiate the four labels for exceptional innovations, especially for operationalization in quantitative studies. Even though these dimensions have been put forward in other studies (Ahuja and Lampert, 2001), we, first, confirm this pattern empirically through a systematic analysis of definitions of the most common innovation labels, and second, also show how the labels are positioned within the framework.

The remainder of the chapter is structured as follows: After a review of the literature (2), we explain the applied methodology (3). Our results (4) and their discussion (5) follow before we conclude in the last section (6).

2.2 Innovation concepts: interchangeability and systematization

In the economic literature, (technological) novelties are most frequently addressed by the labels *invention* and/or *innovation*. *Invention* is usually either explicitly or implicitly defined as 'non-commercial' or 'not yet commercialized' (Ahuja and Lampert, 2001; Arts, 2012; Dahlin and Behrens, 2005; Garcia and Calantone, 2002). An *innovation*, by contrast, is considered to be a novelty that contains new knowledge (out of the pool of new knowledge stemming from the inventions) which 'has proven its relevance for the market economy' (Lundvall, 2016, p. 142). These definitions lead to the 'consensus in the literature that innovation is an outcome of new knowledge' (Forés and Camisón, 2016, p. 1) and that *innovations* are commercialized *inventions* (Ahuja and Lampert, 2001; Hill and Rothaermel, 2003; Schoenmakers and Duysters, 2010) – a definition which is either explicitly emphasized in the literature or implicitly indicated (Arts, 2012; Arts et al., 2013). As our principal goal is to distinguish the different labels assigned to *inventions* and *innovations* and to outline the labels' ambiguities, we do not further stress this particular differentiation. In most of the literature, the difference between *invention* and *innovation* seems to be at least implicitly clear. In contrast, the distinction within the group of so-called 'exceptional innovations' (Kovacs et al., 2019) is more difficult. In the following, we explain how the innovation labels are often used interchangeably and why it is difficult to distinguish them. The focus, for a matter of simplicity, lays on the label *radical* and on how to distinguish it from others. We select it, because it is the most widely used label for 'exceptional innovations' in the business and economics literature.

2.2.1 The interchangeable use of innovation concepts

Innovation labels, when first introduced by an author have a specific meaning. The author wants to emphasize some features of an innovation that have not been touched upon by other labels. As an example, Bower and Christensen (1995), when they first introduced 'disruptive innovation', referred to old technologies that are simplified and adapted to increase demand in the part of the market where existent products do not. Entrants introduce these new products in the market, while incumbents are still offering higher quality products. Eventually, through further innovations and gains in market shares, the former are able to create new business models and consequently completely 'disrupt' the industry Christensen, Johnson, and Rigby (2002), Markides (2006). Other pre-existing terms were not considering the simplification of a technology for marketing reasons as one of their main features. Therefore, Bower and Christensen (1995) identified examples of real innovations with exactly this feature and coined the label 'disruptive innovation'.

Once the label started to diffuse, other researchers used disruptive as a term closely related to 'radical innovation'. Hervás-Oliver, Albors-Garrigos, Estelles-Miguel, and Boronat-Moll (2018, p.1388) use *disruptive* as a characteristic of 'radical innovation', instead of considering it as specific innovation label in itself. They highlight how 'radicalities' can lead to disruption: 'Radical innovation' refers to technological discontinuities that incorporate new knowledge that destroys the value of incumbent systems and technologies in the marketplace'. Hao and Feng (2016) claim that radical innovations lead to changes in the existing way of thinking, which introduces a disruption of an established technological trajectory. In these two cases it is clear that the term "disruption" is used to identify events happening in technological domains after the introduction of a radical innovation. This is a usage of the term "disrupt" has not been considered originally by Bower and Christensen (1995) whom coined the term. Moreover, authors often use *radical* and *disruptive* as synonyms increasing the confusion around these two labels (Colombo, Franzoni, and Veugelers, 2015; Dijk, Wells, and Kemp, 2016; Kaplan, 1999).

Another prominent example is dealing with three labels that can be used either as separately with different meanings or as synonyms: 'radical innovation', 'discontinuous innovation' and 'breakthrough innovation'. 'Discontinuous innovation' is often regarded as the spark introducing a new technological path (Büschgens et al., 2013; Kassicieh, Kirchhoff, Walsh, and McWhorter, 2002; Lynn, Morone, and Paulson, 1996). However, it is also used as a characteristic of 'radical innovation', as in the above quote of

(Hervás-Oliver et al., 2018), or as a synonym for 'breakthrough innovation'. For example, the novelty introduced by 'radical innovations' can be defined as large and breaking with the existing paradigm (Kemp, 1994; Tripsas, 1997). Therefore, this characteristic of "breaking with the existing paradigm" is exactly named by different authors as *discontinuous* (O'Connor, 1998; O'Connor and Ayers, 2005). Moreover, as an example, (O'Connor, 1998) uses the term *discontinuous* as a synonym for *breakthrough*.

Similarly, Ayres (1988) describes the concept of 'breakthrough innovation' as the process to overcome a technological bottleneck, opening possibilities for further innovations. However, *breakthrough*, is also often used either as a synonym for *radical* (Arts et al., 2013; Della Malva and Riccaboni, 2015; Henkel, Rønde, and Wagner, 2015; Schoenmakers, Duysters, and Vanhaverbeke, 2008) or as a specific characteristic associated with a radical innovation, the so called "breakthrough-like" character (Ahuja and Lampert, 2001; Steenhuis and Pretorius, 2017).

Even though labels such as *radical* and *incremental* should be clearly delineated, because they are located at opposite ends of the continuum of the degree of innovativeness (Ettlie, Bridges, and O'keefe, 1984; Schoenmakers and Duysters, 2010), some overlaps still remain. Incremental innovations are commonly described as improvements, small adjustments or further developments of an existing technology or product (Arts et al., 2013; Arts and Veugelers, 2015; Dewar and Dutton, 1986). However, Garcia and Calantone (2002) show how scholars interpret the degree of radicalness that is embedded in an innovative activity differently: "[T]he same innovation can be labeled on either ends of the scale of innovativeness depending on the researcher" (p. 118). Referring to the electric typewriter, which replaced the manual one, they point out that authors with a market perspective and practitioners would rather consider it *radical*, whereas authors with a technological perspective would regard the changes as rather *incremental*. Thus, the same innovation is labeled differently based on its impact on the technological (*incremental*) or on the market level (*radical*). This different labeling based on the type of characteristic considered generates confusion between the two concepts.

In this section we pointed out that innovation labels are often used interchangeably or as a specific characteristic of other labels. These practices are not wrong per se. However, the ambiguous application of innovation labels creates confusion among researchers and practitioners that approach innovation studies. Other scholars have noticed the same patterns in the literature and tried to systematize innovation labels. We provide a review of these studies in the next subsection.

2.2.2 Literature on systematization of innovation concepts

Previous attempts, to systematize innovation labels, mainly focus on identifying innovations by using different characteristics (Garcia and Calantone, 2002; Gatignon et al., 2002; Linton, 2009). More recently, Kovacs et al. (2019) systematically review the definition of the labels. Here we revise these studies and we explain how our chapter is different and contributes into the existing literature.

Garcia and Calantone (2002) provide a framework for the theoretical operationalization of product innovation by grouping innovations into *radical*, *really new* and *incremental*. They argue to differentiate between the macro level (industry, world) and the micro level (firm) and between changes in technology versus changes in marketing. Accordingly, only radical innovations affect all dimensions, whereas really new innovations affect at least either technology or marketing on both the micro and the macro level, and incremental innovations only affect the micro level. Gatignon et al. (2002) systemize innovations by identifying three dimensions: The locus of an innovation, its type and its characteristics. Locus and type are mainly defined by a product's architecture and position within a system (e.g., core versus peripheral subsystem in a greater system, such as a car). Characteristics also comprise the innovation's magnitude and effect (p. 1105f.). Regarding the latter, they find that the distinction between radical and incremental innovation does not correspond to other common dichotomies, such as competence-enhancing versus competence-destroying or architectural versus generational innovation. All of these represent different dimensions in the description of an innovation. More generally,Linton (2009) puts forward a distinction between innovation inputs and outputs and the importance of the 'unit and level of analysis'. Among others, latter refers to the different perception of the same innovation as either radical or incremental, depending on the perspective, as outlined before.

More recently, Kovacs et al. (2019) investigate origin and usage of innovation labels. They show that the intellectual origin of the four labels for exceptional innovation tends to describe either their degree of novelty (*radical* and *discontinuous*) or their effects (*breakthrough* and *disruptive*). Contrary to these empirical findings, Sood and Tellis (2005, p. 153) claim: 'Many terms, such as "revolutionary," "disruptive," "discontinuous," or "breakthrough," [. . .] define an innovation in terms of its effects rather than its attribute'. However, according to Kovacs et al. (2019), scholars tend to use both novelty and impact to describe and define a label. This might boost the interchangeable use we highlighted earlier.

In order to reduce ambiguity, Kovacs et al. (2019) systemize innovations in a two-by-two matrix along the axes of novelty and impact, based on a content analysis of 100 highly cited papers. Therein, *incremental* is the only label solely occurring in the quadrant of low novelty and low impact, whereas the four labels for exceptional innovations are either always novel (*radical* and *discontinuous*) or always impactful (*disruptive* and *breakthrough*) but varying in the other dimension (Figure 2.1). Though clearly advancing the understanding of origin and usage of common innovation labels, this classification does not allow for further differentiation of innovations, such as disruptive and breakthrough innovation. Moreover, all of the previously mentioned studies focus on specific and few characteristics of innovation labels, whereas their specific categorization is important to observe all possible different facets. The consideration of innovation inputs, a more nuanced description of characteristics (beyond the degree of novelty), as well as a further distinction within the effects, might enable to characterize not only single innovations, but also to define innovation labels more precisely.

By combining the systemic framework along inputs, characteristics and effects with a more in-depth study of innovation labels' definitions in over 500 scientific articles we are able to improve current innovation typologies and the delineation of the six labels investigated. In this sense, we extend

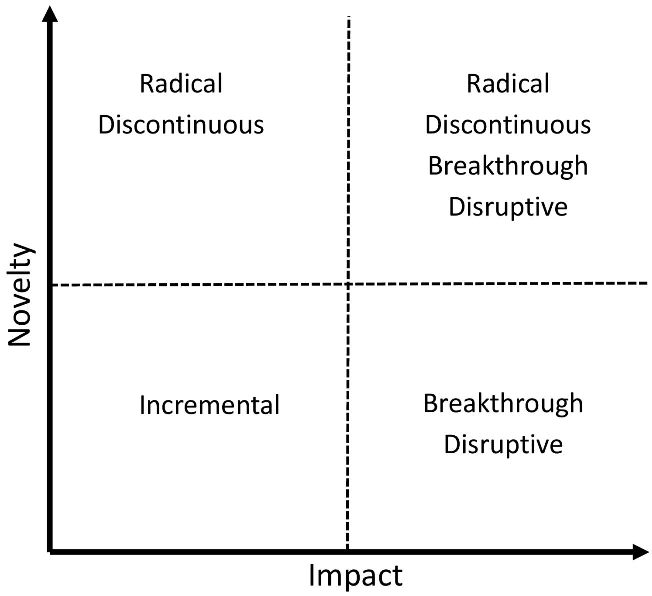


Figure 2.1: Dimensions of "exceptional innovation" in Kovacs, Marullo, Verhoeven, and Van Looy (2019). Source: Own representation according to Kovacs, Marullo, Verhoeven, and Van Looy (2019)

the literature on the categorization of innovation labels by providing a novel framework and a more precise delineation of the labels.

2.3 Method

To specify the most prominent innovation labels (see section 2) and to highlight the inconsistencies in their distinction from another, we analyze how they are defined in a variety of peer-reviewed publications. We obtain our core dataset by conducting a manual, quantitatively oriented analysis of the relevant literature. Computational text analysis is improving quickly but still lacks precision when it comes to context (Arts, Cassiman, and Gomez, 2018). Since we focus on wording, we maintain a conservative approach of manual text coding. The relevant literature is obtained by a Web of Science (WoS) search for the labels *radical*, *discontinuous*, *disruptive*, *breakthrough*, *continuous*, and *incremental* alongside *innovation(s)*, *invention(s)*, *technol-*

ogy(ies) or *technological change* appearing as a topic of the document. We choose the topic instead of the title to increase the number of hits while preserving the relevance of the keyword for the content of the document. The 5,042 documents found are reduced by filtering only documents belonging to the broader category of the social sciences (2,629 documents) (Figure 2.2). These fields are more likely to provide definitions and discussions of the innovation terminology. Subsequently, the set is reduced by filtering for 'articles', 'proceeding papers', and 'book chapters' to consider actual scientific contributions (no news outlets, editorial material, etc.). Further, we exclude documents with no or few citations. We believe that more influential work also shaped the use of innovation labels to higher degrees. Consequently, all documents belonging to the 25 percent of highest citations within arbitrarily chosen groups of years (see Figure 2.2 – 'citation filter') are selected. Nevertheless, some older articles receive high citation counts, wherefore we include all articles with more than 30 citations even if the 75 percentile is higher.

In the subsequent review of the remaining 716 documents, we search for each innovation label that was assigned as a topic of the document and check for definitional phrases around the label's occurrences (Figure 2.2 – 'first coding'). In a group meeting of the three authors with another four members of the research group, we discussed the joint approach to coding. Based on the systematic divisions of Linton (2009), Kovacs et al. (2019) with inputs as necessary condition for a certain type of innovation, its very nature (features, such as the degree of novelty) and its outputs (or effects), we reached agreement about assigning each phrase containing definitional elements about the respective innovation label to one of the three phases *Requirements* (Input), *Features* (Content), or *Effects* (Output). In this way, further and other systematizations were excluded in advance but ensured that all codes could be clearly assigned. The following phrases exemplify the coding procedure:

"To develop radical innovations, firms depend on technological and market related capabilities. One important market related capability is the competence to involve the 'right' users at the 'right' time in the 'right form'." (Lettl, 2007, p. 53)

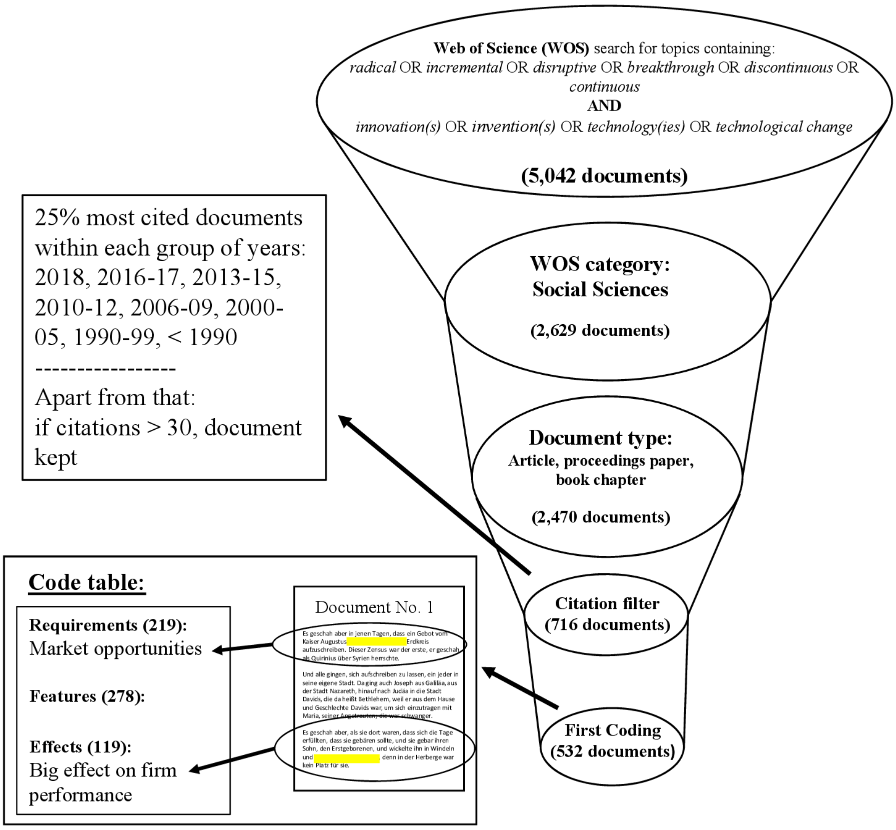


Figure 2.2: Data retrieval and coding

This paragraph is coded as *"market opportunity"* and is assigned to the *requirements* phase. It is "market related" and describes the involvement of "the right users at the right time", which refers to opportunity detection. Such a capability can be regarded as a requirement or cause (input) of radical innovation.

"Most innovations in operational Business Units (BU's) are incremental and build on established products and technologies and exploit the current knowledge base of a company. They are mere improvements in the product to reinforce the current viability of the company in a particular business or market" (Berends, Vanhaverbeke, and Kirschbaum, 2007, p. 316)

Table 2.1: Number of applicants in selected regions

Subject	Object	Intensity	Direction	Perspective
Describes *what* the code is about (e.g. *performance*, *structure*, *power*)	Describes to *which entity* the code is associated (e.g., *market*, *organization*, *technology*)	Describes whether the code specifies an *intensity*, such as *high* or *low*	Describes an additional subject or adjective like *positive*, *negative*, *change* or *creation*	Describes whether the code is about something *internal* or *external* to the innovating entity

Note: The first-round codes are assigned to these dimensions to aggregate more representations of the innovation labels' definitions

This is, among others, assigned to the features and coded as *'small product modification or improvement'* as it describes the content of an incremental innovation.

"Moreover, radical innovations can be a key to firms opening new markets and can have a significant effect on overall firm performance" (Green, Gavin, and Aiman-Smith, 1995, p. 203)

This example can clearly be identified as an *effect* (output). Moreover, the effect is described as "significant", why we code it as *'large effect on firm performance'*.

532 documents contain definitional information. From these, we obtain 219 distinct codes (803 mentions) for requirements, 231 codes (2,196 mentions) for features, and 119 codes (730 mentions) for effects (see Table A3 for a complete list). In total, we have 3,729 mentions of the six innovation labels (*57% radical*, *23% incremental*, *8% breakthrough*, *5% disruptive*, *5% discontinuous*, and *2,5% continuous*).

The inductive coding results in many codes occur rarely. However, they are very similar to others. For example, *'financial benefit to the firm'* and *'greater likelihood of, or longer business survival'* both refer to positive effects on the innovating organization. To systemize and aggregate the codes for an easier quantitative assessment, the research group engaged in a second round of discussions (and subsequent coding). Thereby, five dimensions were defined to which the first-round codes could be assigned with a specific expression. The result (Table 2.1) is strongly oriented towards linguistic, grammatical components.

Table 2.2: Second round of coding: Assignment of codes to dimensions

Code	Phase	Dimension					Innovation Label (No. of Occurrences)	
		Subject	Object	Intensity	Direction	Perspective	Radical	Incremental
Market opportunities	Requirements	Structure	Market	Neutral	-	External	9	1
Small product modification or improvement	Features	Novelty	Product	Low	Improvement	Neutral	1	81
Big effect on firm performance	Effects	Performance	Organization	High	-	Internal	20	1

Notes: Empty spaces are left if the code does not contain the respective dimension. The labels 'radical' and 'incremental' are chosen exemplarily. Note that, e.g. 'market opportunities' is an external requirement, whereas 'opportunity detection' is internal.

Based on the description of these five dimensions, for each phase (*requirements*, *features*, *effects*) a team of two members of our research group assigned each first-round code to an inductively generated expression in each of the five dimensions. For example, when the code describes an effect on performance (of the firm, the market, etc.) the code is assigned the expression *performance* in the dimension *subject*. In the data aggregation process, each dimension was given the minimum number of distinct expressions needed to preserve important differences. In some cases, especially with very general codes (e.g., *'change'*), not all dimensions could be filled. As can be seen in Table 2.2, the first-round code *'market opportunities'*, for example, is neutral in its *intensity* and does not have a *direction*.

In a second step, the results were passed on to another team, which in turn created its own assignment to expressions in the five dimensions based on its own inductive expressions. Ambiguous assignments and expressions were then discussed in the group until a common solution was found. Table 2.2 exemplifies the assignment for one code of each phase. For example, the code *"big effect on firm performance" (effects)* is assigned to the *subject 'performance'*, the *object 'organization'*, the *intensity 'high'* ("big effect"), the *direction 'neutral'* as it is not further valuated, and to *'internal'* as it describes the *perspective* of the innovating firm.

For a quantitative differentiation between the labels, we aggregate the information contained in Table 2.2 according to matching expressions in the

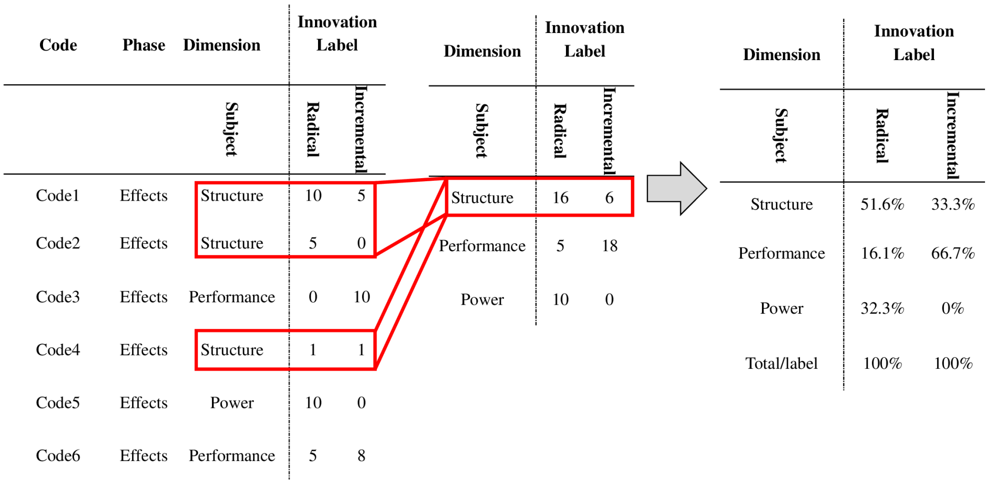


Figure 2.3: Calculation of label-wise shares over expressions of a dimension (here: subject)
Notes: Irrespective of the original Code (Code1 – Code6), the expressions (structure, performance, and power) are aggregated and the number of occurrences is summed up.

different dimensions. If we are, for example, interested in the potential of the dimension *subject* to discriminate between the *effects* of the different innovation labels, we aggregate the codes of the *effects* phase to their expressions in the dimension *subject* regardless of their assignment to the other dimensions (Figure 2.3). We then calculate the share of each expression as a label-total. Hence, we observe and interpret differences in the distribution across the expressions (Figures A1-A3). When all dimensions (*subject*, *object*, *intensity*, *direction*, *perspective*) are combined, the 569 first-round codes (Column 'Code' in Table 2.2) are aggregated into 350 unique combinations of expressions along the dimensions (unique combinations of all 'Dimension' columns in Table 2.2). For example, the codes *'revitalization of incumbents'* and *'value creation for the whole industry'* are both aggregated to the expressions *'performance - industry - neutral - positive - external'* in the respective five dimensions. Even though the codes do not have identical meaning, they refer to relatively similar phenomena.

Table 2.3: Share of occurrences between input/content and output (by label)

	Rad	Disc	Disr	Bt	Con	Inc
Requirements/ Features	1682 (79%)	140 (77%)	141 (73%)	212 (75%)	80 (83%)	744 (88%)
Effects	445 (21%)	42 (23%)	52 (27%)	71 (25%)	16 (17%)	104 (12%)

Note: Requirements and Features are aggregated and compared against Effects (as comparable with Kovacs, Marullo, Verhoeven, and Van Looy (2019), comparing the input (novelty) orientation of labels with the output orientation.

2.4 Results

The results section is structured as follows: First, in comparison with Kovacs et al. (2019) we show the distribution of codes between the phases (requirements, features, effects) to identify which labels are more input- or output-associated in the literature. Next, to get an impression of overall similarities and differences between the labels we display the cosine similarity between the six innovation labels, based on their distribution over the 350 unique codes that result from the aggregation in the second round of coding (also divided into *requirements*, *features* and *effects*). Finally, to identify the origin of these differences, the central distinguishing characteristics are evaluated and combined into a summarizing table. The evaluation is based on Figures A1 to A3, which display the label-wise shares of expressions in the different dimensions (as exemplified in Figure 2.3). Further details, such as most frequent codes per dimension and label (Table A2) as well as the complete code table (Table A3) can be found in the appendix.

Looking at the frequency of codes divided by phases, the shares slightly reflect the higher output orientation of *breakthrough* and *disruptive*, contrary to *radical* and *discontinuous* (Table 2.3) as found by Kovacs et al. (2019), although few differences are statistically significant (Table A1). Hence, even though the distribution to a certain extent reflects a differentiation between the labels for rather ordinary and more exceptional innovations, it does not allow a clear differentiation between different exceptional innovations. Thus, it justifies a deeper analysis of the underlying characteristics.

Using all 350 unique codes retrieved from the second round of coding the requirements of *radical* show a high similarity not only with *breakthrough* but also with both labels for rather ordinary innovations (Figure 2.4). This

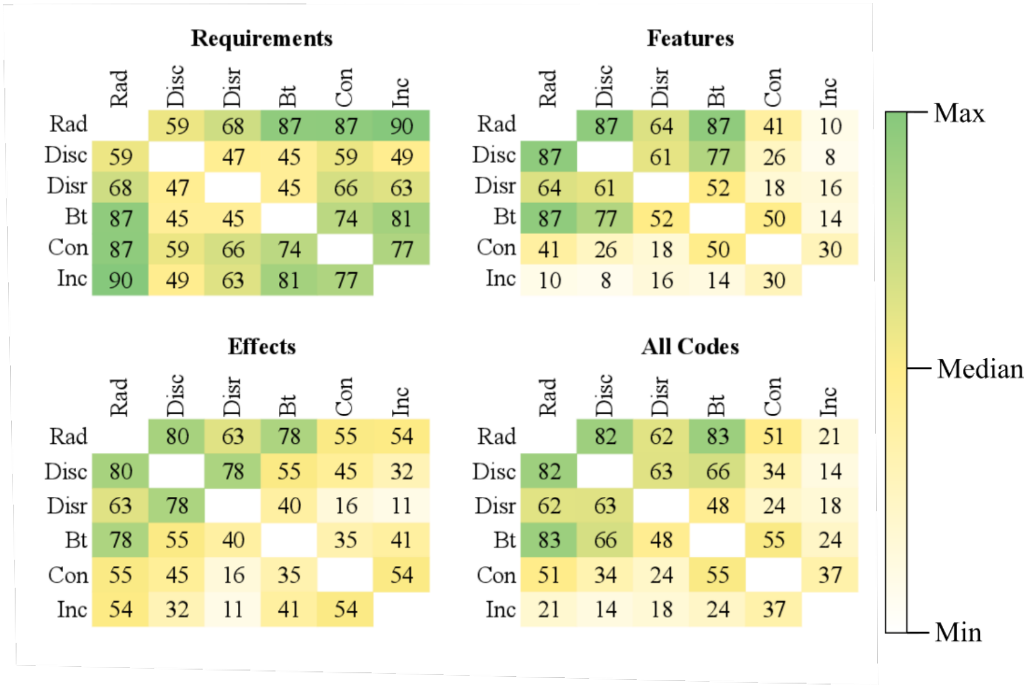


Figure 2.4: Cosine similarity (in percent) between innovation labels (by phase)
Notes: Values indicate similarity (in percent) of each two labels based on the overlap in (the frequency of) association with the 350 unique codes

overlap is far lower (especially with *incremental*) in *features* and *effects*. Hence, the same conditions and other requirements might lead to innovations with extremely different effects. In the *features*, the difference between exceptional and ordinary innovations becomes most apparent, although *continuous* is more similar to the exceptional innovations than *incremental*. In terms of *features* and *effects*, both *breakthrough* and *discontinuous* seem to be more strongly related to *radical* than *disruptive*. Moreover, while *discontinuous* and *disruptive* are associated with a different semantic origin (input- vs. output-related, respectively) (Kovacs et al., 2019), their *effects* have a high similarity, equally as high as the one between *breakthrough* and *radical*. With the similarity based on all codes together, both *discontinuous* and *breakthrough* are most similar to *radical*, despite having less overlap individually. Showing overall lower similarity with other labels, *disruptive*, *continuous*, and *incremental* seem to be more distinct. Surprisingly, *continuous* has a higher overlap in codes with *radical* and *breakthrough* than with *incremental*, the other label for a rather ordinary innovation. In the following, we identify the decisive characteristics in each phase to understand the observed similarities and differences between the labels.

For all six innovation labels, *requirements* relate mostly to resources and structures (*subject*, Figure A1). Likewise, external sourcing (e.g., for new knowledge) is not regarded as particularly important for generating exceptional innovations compared with rather ordinary innovations (*perspective*, Figure A1). However, there are also clear differences: *Disruptive* is associated with a stronger market-relation (*object*, Figure 6; code: *'market opportunities'*). In this sense, firms pursuing *disruptive* innovations are keen to develop new marketable products to achieve or maintain competitive advantage (Pandit, Joshi, Gupta, and Sahay, 2017). *Breakthrough* is strongly related with the knowledge dimension (*object*, Figure A1). In order to successfully develop *breakthrough* innovation according to the original codes and to the literature, firms should rely on *'external knowledge'* sources (*object-perspective*, Figure A1; (Phene, Fladmoe-Lindquist, and Marsh, 2006) or draw from different knowledge sources (code: *'knowledge breadth'*, Srivastava and Gnyawali, 2011). Moreover, *continuous* is strongly associated with specific organization-internal structures, such as flexibility and openness (*direction*, Figure A1). In fact, to develop *continuous* innovation, dynamic capabilities (such as: knowledge creation, absorption, integration and reconfiguration) are considered necessary assets (Verona and Ravasi, 2003). Nevertheless, altogether the definitions of different innovation labels differ much less in their *requirements* compared with their *features* and *effects*, as validated before (Figure 2.4).

Even though all innovation labels are to the largest degree described by their novelty (*subject*, Figure A2), the precise extent and quality varies. *Breakthrough*, for example, is more related to its knowledge components and technology (*object*, Figure A2), with *'multiple knowledge sources'* as the respectively most frequent code. According to the literature, to develop *breakthroughs* firms should collaborate with heterogeneous partners, which permits them to draw knowledge from different sources (Qi Dong, McCarthy, and Schoenmakers, 2017). Moreover, among the exceptional innovations, *breakthrough* is least clearly associated with progressive features (*direction*, Figure A2). Accordingly, breakthrough innovations seem to feature combinations of existing knowledge or novelties resulting from deepening of current knowledge and capabilities as well. *Discontinuous* is most strongly associated with novelty in technology (*object, subject – without 'low'*, Figure A2). As shown by Birkinshaw, Bessant, and Delbridge (2007), in order to pursue discontinuous innovation firms in high-tech industries should implement new technologies to remain competitive with other companies. Contrarily, *radical*, *disruptive*, *incremental* and *continuous* relate relatively more to market and product features (*object*, Figure A2), even though within, the contrast between *radical* and *incremental* becomes clear (*subject*, *direction*, Figure A2): While the former is described by dissimilarity, uncertainty, and associated with negative features (original codes: *'market and or consumer uncertainty'*, *'business inexperience'* and *'unfamiliar market'*), the latter is described by the opposite (original codes: *'driven by consumer needs'* and *'in a well-established market'*). *Disruptive* differs from the other exceptional innovation labels because of the particular importance of new entrants to the market with initially lower performance of the products (*subject*, *direction*, Figure A2). Disruptive innovations are said to initially target small niches of the market and to redefine old technologies (Ansari, Garud, and Kumaraswamy, 2016; Govindarajan, Kopalle, and Danneels, 2011). Finally, *continuous* is more strongly described as dissimilar than *incremental* (*subject*, Figure A2), but this dissimilarity relates more to products and processes (original code: *'new product(s) and services'*) compared with technology and the market (for the 'exceptional' innovations) (*object*, Figure A2).

The clearest delineation between exceptional and ordinary innovations is visible in the extent of their *effects*. *Radical* (code: *'big effect on firm performance'*), *discontinuous* (code: *'competence destroying'*), *disruptive* (code: *'failure, destruction of established firms'*), and *breakthrough* (code: *'high profitability'*) are to a considerable degree associated with high impact, whereas *continuous* and *incremental* are not (*intensity*, Figure A3). Furthermore, *radical* and *breakthrough* are both associated with more positive effects (*direction*, Figure A3), but the former is more strongly affecting the market, whereas the latter rather affects technology (*object*, Figure A3). The firms developing radical innovations gain competitive advantage (Shahin, Barati, and Geramian, 2017) whereas breakthrough innovations rather describe the creation of novel technological combinations shaping industry trajectories (Kaplan and Vakili, 2015). *Disruptive* and *discontinuous* are associated with negative effects (*direction*, Figure A3), with the former strongly relating to changes in the market, whereas the latter also significantly affects the innovating firm (*object*, Figure A3). When a disruptive innovation is introduced in the market, incumbents face new challenges, possibly leading to a crowding-out effect (Bergek, Berggren, Magnusson, and Hobday, 2013). According to the literature, the focus of discontinuous innovations lies on the outcomes of single firms even though these firms face an initial reduction in performance and the rewards are distant in time (Birkinshaw et al., 2007). By contrast, *incremental* is strongly described by the positive effects on the firm and on performance (of the firm) (*object – direction, subject – direction*, Figure A3), for example, by creating value, which increases profitability and strengthens the market position. However, compared to the more 'exceptional' innovations, these positive effects are characterized by a relatively low magnitude and they become apparent only in the short run (Benner and Tushman, 2002). Finally, contrary to *incremental*, *continuous* shows a share of external effects comparable to the labels for exceptional innovations (*perspective*, Figure A3). However, due to the small sample size, the results for *continuous* should be treated cautiously.

Altogether, *features* and *effects* are much more useful to delineate the different innovation labels than their *requirements*, even though the discussion about the four 'exceptional' innovations is more focused on the output in contrast to the rather 'ordinary' innovations. However, confirming the results of Kovacs et al. (2019), we find no significant difference in the input/content vs. output orientation among the 'exceptional' innovations.

2.5 Discussion

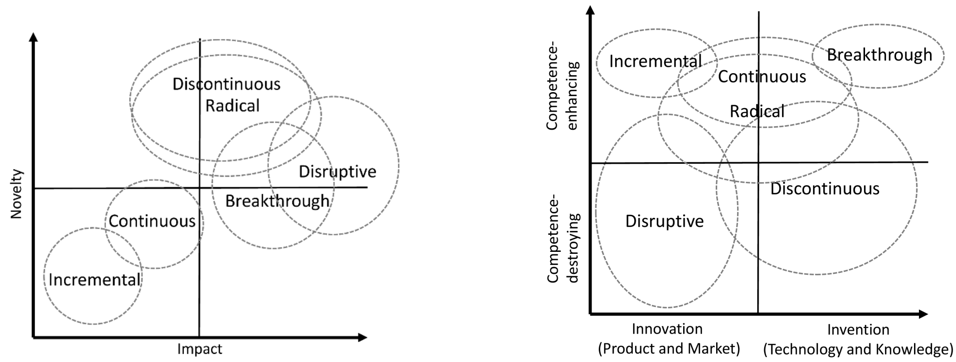
Our first and broad results largely correspond to the innovation typology by Kovacs et al. (2019) presented in Figure 2.1, with the central dimensions of novelty and impact. The label *incremental* is clearly described as less novel and less impactful. On the other end, the more 'exceptional' innovations can be divided into the more novelty-oriented (*radical* and *discontinuous*) and the more (high) impact-oriented (*disruptive* and *breakthrough*) labels: *radical* and *discontinuous* have lower shares of occurrences for specifically

Table 2.4: Summary of the quantitative text analysis

	Requirements	Features	Effects
Rad	*Resource* and *structural* requirements. *Internal* (human capital) and *external* resources (knowledge and interaction) equally important.	Described by *novelty* and *dissimilarity* and associated with the *technology-, market- and product*-level. Has also negative features (high risks and costs)	*Higher* impact, specifically on *performances* and *structures*. *External* effects. Strong *market* effects, but also on the *firm*. Besides leading to *change* and *creation* also *positive association* of effects.
Disc	*Progressive structures* (*internal and external* and related to *change* and *creation* (*novelty*). *Changes* in human *resources* and *external* changes (environment) important.	Described by novelty (of the inherent technology). High dissimilarity to the existing and highest share of uncertainty.	*Higher* impact, especially on *structures*. Strong *market* effects but also on the firm. Effects rather *external* and substantial share of *negative* associations.
Disr	*Resource* and *structural* requirements, specifically *market*-related. *External* resources and *flexibility* particularly important as well as *new firm strategies*. *Changes* in *policies* (e.g., regulations) can be required.	Described by *novelty*, but also the way of *introduction* (by young and small firms in niches of the market). Particularly *negative* features (initially worse performance).	*High* impact. *Structures* and *performance*, but also *capabilities* affected. Strongly associated with the *market* and with *negative* effects (especially for established companies and knowledge).
Bt	*Resources* and *structures* (mostly *knowledge*-related) important. Besides *change* and *knowledge breadth* also *deepening* of existing capabilities.	Described by *novelty*, but also the *search process* and *resources* (especially *knowledge* and *technology*). Associated with *existing knowledge* and its *recombination*.	*Higher* impact. *Performance* and *structures* affected. Besides effects on *market* and *firm*, particularly affecting (future) *technology*. More related to *creation* than to change and (therefore) *positive* association.
Con	*Structures* (internal) more important than resource-related requirements. *Change*, *flexibility* and *openness* (regarding human capital and *interaction* required.	Described by *novelty* as well as the *search process*. Mostly about new or adapted *products* and *processes* which can be *similar* or *dissimilar* to the existing.	*Lower* impact. Related to *power* and *performance* of the innovating *firm* in the market. Also *external* effects
Inc	*Structural* and *resource* requirements and strongly associated with *knowledge* and *interaction*. Even though *conservative* requirements dominate (persistence, depth, centralization), *external* sources (e.g. of knowledge) are particularly important	Described by *novelty* as well as the *search process*. Features relate to *products* and *processes* and *rather low degree of change*. Comparably low risks and costs.	*Lower* impact. Related to the *performance* and *power* of the innovating *firm* in the *market*. Rather *internal* effects, but *highly positive* association.

'high' effects, but a stronger relation to novelty as descriptive dimension for their *features* as well as an overall slightly higher percentage of rather 'progressive' *requirements* and *features* (Figure 2.5a). *Continuous*, which we additionally consider, tends to describe 'ordinary' innovations, but not as clearly as *incremental*. More importantly, however, our results highlight at least two further considerations for the evaluation and classification of innovation concepts.

First, according to our results and in contrast to Kovacs et al. (2019), the differences between the labels are not so pronounced that either of the dimensions 'novelty' and 'impact' alone would be sufficient to mark a clear-cut differentiation. Our results highlight two additional dimensions along which the labels need to be differentiated (Figure 2.5b). On the one hand, they can be categorized as more product- and market-related versus more knowledge- and technology related. On the other hand, their effects can be categorized as rather positive or negative. The first dimension has already been stressed in several publications, though for a limited number of innovation labels: Ahuja and Lampert (2001), for example, divide impactful innovations into *radical* (market impact) and *breakthrough* (technological impact). By contrast, Rosenkopf and Nerkar (2001) mention that radical and breakthrough innovations are both valuable from the market and technology side. Our findings suggest that *disruptive* and *incremental* are clearly related to the market- and product level, whereas the association is unclear for *discontinuous* and *radical*. Even though *discontinuous* is strongly linked to technological *features*, the *effects* are associated with the market to a considerable degree, based on our results. *Breakthrough*, by contrast, has a clear technology- and knowledge association. Therefore, it refers more to the technical invention than to marketed products, which suggests a more general distinction between inventions and innovations (Figure 2.5b). As stated in section 2, inventions are technical advances that are not yet commercialized (Ahuja and Lampert, 2001), whereas innovations are products or processes that are relevant for the market (Lundvall, 2016). Accordingly, *breakthrough* is closer to the knowledge and technological dimension and thus only impacts the technical trajectory, whereas *disruptive* mostly refers to the market dimension. The frequent association of *breakthrough* with invention further underlines this characterization, in contrast to *disruptive*,



(a) Innovation typology based on impact and novelty

(b) Innovation typology based on direction and entity of impact

Figure 2.5: Innovation typologies (circles around the labels refer to how widely or narrowly they are defined in the literature)

which is usually associated with innovation. The second dimension, the positive or negative connotation of effects, is less present in the discussion of innovation concepts. Nevertheless, the notion of 'competence-destroying' or 'competence-enhancing' effects of innovations has been stressed, for example, by Cooper (2000), Henderson (1993), Kostoff, Boylan, and Simons (2004), Lettl, Herstatt, and Gemuenden (2006).

However, these studies mostly contrast concepts for exceptional and ordinary innovation. Our data reveals that effects of incremental innovation are the most positively connoted in comparison to exceptional innovations, albeit *breakthrough* is also associated with mostly positive effects. Moreover, *disruptive* and *discontinuous* tend to be more strongly associated with negative effects, apart from the positive effects for the innovating company itself. The proportions of positive and negative associations lie between the other labels for *radical.*

Second, innovation labels are defined by and described with specific characteristics to map distinguishable innovation concepts. This distinction is particularly important when these labels are used to operationalize innovation in empirical studies. Many quantitative studies use large data sets such as patent data. The dimensions of novelty and impact are frequently used in these studies to distinguish exceptional from ordinary innovations. Within the group of exceptional innovation, however, empirical approaches usually do not differentiate. *Breakthrough*, for example, is mostly measured on the basis of the impact (patent citations) (Kaplan and Vakili, 2015; Phene et al., 2006). Regarding the other dimension, a different label, *atypical*, has been used several times to capture particularly new innovations or innovations that deviate from existing ones (Kim, Cerigo, Jeong, and Youn, 2016; Mewes, 2019; Uzzi, Mukherjee, Stringer, and Jones, 2013). *Radical*, on the other hand, is operationalized based on both dimensions, separately or as a combination of both novelty and impact (Dahlin and Behrens, 2005). However, the quality of these dimensions is usually not further specified. Particularly, no differentiation between effects on technological development or the market (and industries) and between positive and negative effects is made.

The positions of the different labels within the frameworks of Figure 2.5 highlight why a clear operationalization might be very difficult: Some labels are rather narrowly defined, such as *incremental* – with low novelty, low impact, related to product and market and associated with positive effects. Others, such as *discontinuous* or *radical*, are much more widely defined in the literature. Operationalization, however, usually is and should be based on accurate indicators for specific characteristics (which a certain type of innovation fulfills) and not on a rather spurious label (see Downs Jr and Mohr, 1976). Researchers need to clarify what innovation characteristics they ought to measure. This concerns, for example, whether the degree of impact, the degree of novelty or both are important in the respective study. Further, a differentiation between (technological) inventions and (marketed) innovations and the direction of their effects (rather competence-enhancing or competence-destroying) can be very important for policy implications derived from innovation studies. It clearly makes a difference whether the investigated type of innovation has a big negative impact on established structures, or whether it enables all industry or market actors to improve their products and processes. The same holds for the status as either a technological advancement (which might affect further patenting) or as a marketed product (which already affects the industry, its structures and its customers).

Following these considerations, the innovation literature might offer a concept (and label) that describes, or at least includes, an innovation with the selected characteristics. However, the respective label might be used in the literature in several ways or with overlaps with others.

2.6 Conclusion and Limitations

The aim of this chapter was to bring more clarity in current innovation typology by quantitatively assessing the decisive characteristics of prominent innovation labels based on their use in the innovation literature. In another recent paper, Kovacs et al. (2019) have already examined the bibliographic origins of four labels for exceptional innovations. In particular, they considered the use of the dimensions of novelty and impact as descriptive elements of innovation labels. These dimensions largely form the basis of quantitative operationalization of innovation but reflect only to a limited extent the content of some innovation concepts. Moreover, they still yield potential to confound and lead to the use of the labels interchangeably. To further improve the typology of innovation, we examined the definitions of the labels *radical*, *discontinuous*, *disruptive*, *breakthrough*, *continuous* and *incremental* in over 500 scholarly articles. Like Kovacs et al. (2019), we find that the degree of novelty and the impact are key descriptive features of all innovation labels, although their linguistic origins rather belong in either of the two dimensions.

Moreover, we show two additional aspects: On the one hand, it is important to consider whether an innovation is more market- and product-related or technology- and knowledge-related, which can also be referred to as a distinction between innovations and inventions. On the other hand, it is essential to pay special attention to what degree the resulting effects have positive or negative connotations (particularly 'competence-destroying' vs. 'competence-enhancing'). The connotation of innovation labels can be even more relevant when scientific research is transported to the political sphere. However, rarely, one of the innovation labels examined (especially exceptional innovations) can be assigned exclusively and solely to distinct categories. These implications show above all that for an accurate operationalization and, thus, replicability of studies, the existing labels should be used cautiously. As we aim for more clarity in innovation terminology, we refrain from presenting even new labels for the quadrants within our extended typology. Nevertheless, we encourage further research to investigate the decisive characteristics of innovations. Our typology and the additional and more detailed results presented in the appendix present a useful starting point.

Notwithstanding, our study has few limitations. Firstly, we selected a distinct set of innovation labels based on their presence in the innovation literature and on their investigation in the previous study of Kovacs et al. (2019). Other popular labels for exceptional innovations, such as 'architectural' (Henderson and Clark, 1990) are likely to reflect characteristics other than the ones represented by the labels used in our study. Secondly, our quantitative analysis does not consider the research context of the papers from which we code the definitional characteristics. For example, our finding that *breakthrough* as a label for a technological and impactful innovation fits well with its operationalization in quantitative innovation studies might be caused by an overrepresentation of these studies in the definitions of breakthrough in the literature. Thirdly, a bibliographic analysis of the diffusion of the innovation labels might explain how and why certain definitional characteristics are more frequently mentioned than others – an endeavor we leave for our further research. Fourthly, *radical* and *incremental* are very common in many papers included in our analysis. However, the literature mentioning *continuous* or *disruptive* is much more limited, so our findings might be less valid for these labels. Lastly, even though our coding system has been cross-validated, it is possible that other research teams would have conceived of different assignments and therefore produce at least slightly different results. Nevertheless, this chapter contributes to a better understanding and careful use of innovation concepts and respective labels in scientific research.

Future research could validate our innovation typology with additional qualitative studies about the perception and interpretation of innovation labels by both researchers and practitioners. When performing quantitative innovation studies, researchers should carefully consider the appropriate operationalization of the type of innovation they investigate.

Chapter 3

Bridging Technologies in the Regional Knowledge Space: Measurement and Evolution

3.1 Introduction

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

Concepts of technologies with great innovative and transformative potential, such as General Purpose Technologies (GPTs) or Key Enabling Technologies (KETs), build on this idea of establishing or reinforcing connections between different technology fields. GPTs as well as KETs have been identified as sources of economic growth and have attracted the attention of policy makers (Bresnahan and Trajtenberg, 1995; Posada et al., 2015).

This view of interconnected fields of knowledge or technology calls for a network perspective, as proposed in the literature on Product Spaces, economic complexity and Knowledge Spaces (KS) (Kogler et al., 2013; Hidalgo et al., 2007; Hausmann and Hidalgo, 2011). Within such networks, fertile technologies, particularly, serve as bridges with the potential to affect the improvement (new inventions) of connected technologies (Graf, 2012).

We define a Bridging Technology based on its function as a connecting element between many other technologies by being positioned in the center of 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 can be identified within each KS based on their position and functionality. We propose two different definitions of BTs and develop indicators for their identification.

The indicators are inspired by Social Network Analysis (SNA) methods applied to 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, we capture the idea of bridging in a network by Betweenness Centrality (BC). The index is based on the frequency with which 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 Germany with a particular focus on the region of Jena, located in East Germany (former GDR). We choose Jena as a prototype for our methods since it is a strong patenting region and its innovation system has been analysed in several studies (Graf, 2006; Fritsch and Graf, 2010; Graf and Broekel, 2020), allowing us to cross-validate our findings. 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 and to track their development and their change in position in the KS.

We apply both indicators to an analysis of 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 3.3, we provide two alternative definitions of bridging technologies. In section 3.4, 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 3.5, we present results on the technological development of Jena's KS. In section 3.6, 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.

3.2 Literature Review

3.2.1 Structural Change and Innovation

Many studies distinguish between different types of technologies based on their potential impact on structural change and growth. A fundamental distinction is between radical and incremental technological innovations. Radical innovations render existing competences obsolete and redefine the concept of competitive advantage, sometimes by creating completely new industries, in line with Schumpeter's view on "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; Abernathy and Clark, 1985; Scott, 2006). Dosi (1982) uses the concept of technological paradigms to distinguish between continuous changes along existing trajectories and discontinuities that challenge existing paradigms and help to establish new ones. In a subsequent article, Dosi (1988) points out that processes of innovation are local and context dependent. He defines *untraded interdependencies* as competences shared between different sectors that can be seen as *collective assets* of multiple firms established within a region or country. Because of their regional specificity, these interdependencies not only impose restrictions but also open unique avenues for subsequent technology development paths.

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 is 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 and Lambooy, 1999).

3.2.2 General Purpose Technologies and Key Enabling Technologies

Theories on General Purpose Technologies and Key Enabling Technologies make linkages and interdependencies between different fields of technology more explicit (Tushman and Anderson, 1986; Bresnahan, 1986; 2010).

In their seminal study, Bresnahan and 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 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 and Trajtenberg (2004) retrieve the features of GPTs by taking the example of the steam engine. First, GPTs have *general applicability*, which 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 and Gertsen,

2003) that increase efficiency for users and help diffusion in other sectors. In the literature, this third characteristic is called *pervasiveness*, and it is usually used in combination with technological diversification (Malerba and Orsenigo, 1997; Cantner and 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 and Trajtenberg, 2004). All these characteristics create loops in which the better performances of an industry or technology connected to the GPT also creates incentives 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 and Vannuccini, 2017).

From these features, *pervasiveness* and *innovational complementarities* are closely related to the concept of a bridging technology; 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 further advances in the mainstream technology become too costly, whereas new opportunities to connect previously unrelated fields become economically attractive (Malerba and Orsenigo, 1997; Graf, 2012).

Hall and 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 discover 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 does the focal technology benefit by creating linkages with others, but an increase in patenting is also 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. In their definition of GPTs, Bresnahan and Trajtenberg (1995) explain that they could have the ability to *enable* other subsequent advances. In this sense, they can open new possibilities for technical advances without offering final solutions.

An explicit identification of KETs was first proposed by the European Commission (EC), which selected six GPTs aimed at sustaining the competitiveness of European industry in the global economy (nanotechnology, micro and nano-electronics including semiconductors, photonics, advanced materials and biotechnology) (European Commission, 2009). The European Commission (2009) claims that these technologies have unexpressed potentials that should be exploited by the European industry, with the aim to use these KETs within smart specialization strategies. As affirmed by Montresor and 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 above), 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 and 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, Nie, Lin, and Chandrasekaran (2016), who observed challenges that the wireless technology face with 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 because without the fundamental advancement of the existing technology, the realization of the new one is also 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.

3.2.3 Knowledge Space

Studying the inter-relatedness between different industries or technological fields has a long tradition. 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 shows 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, Rumelt, Dosi, and Winter (1994) who show that the growing number of activities performed by US manufacturing firms coincide with an increased coherence between similar industries. Breschi, Lissoni, and Malerba (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 and 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 they remain specialized.

Boschma, Minondo, and Navarro (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 more easily enter 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) use patent data to study how knowledge is distributed in different US cities. 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, Balland, and Kogler (2014) study how existing relatedness can affect the entrance of a new technology in a city, using US patent data. Finally, Balland, Boschma, Crespo, and Rigby (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 they 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 and 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; and they can be granted for very long periods of time and in 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 and 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 and Kim, 2010; Alstott et al., 2017; Yan and 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 and 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 and Luo, 2017). Leydesdorff, Kushnir, and Rafols (2014) and Kay, Newman, Youtie, Porter, and Rafols (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 and Luo, 2017). Several studies use 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 and 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.

3.3 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, 1969). Subsequently, evolutionary economists identify these technologies as GPTs because of their particular characteristics (Bresnahan and 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 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, but what differs is that there is no ex ante identification of a BT. Rather, it is defined by its function within the KS. As such, there can be different BTs in a 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 of 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 3.1 shows a graphical representation of both definitions. The first one (Figure 3.1a) represents a BT (red node) that is connected to many other technologies and is at the center of the network. In the second definition

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

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

Figure 3.1: Bridging Technology Definitions

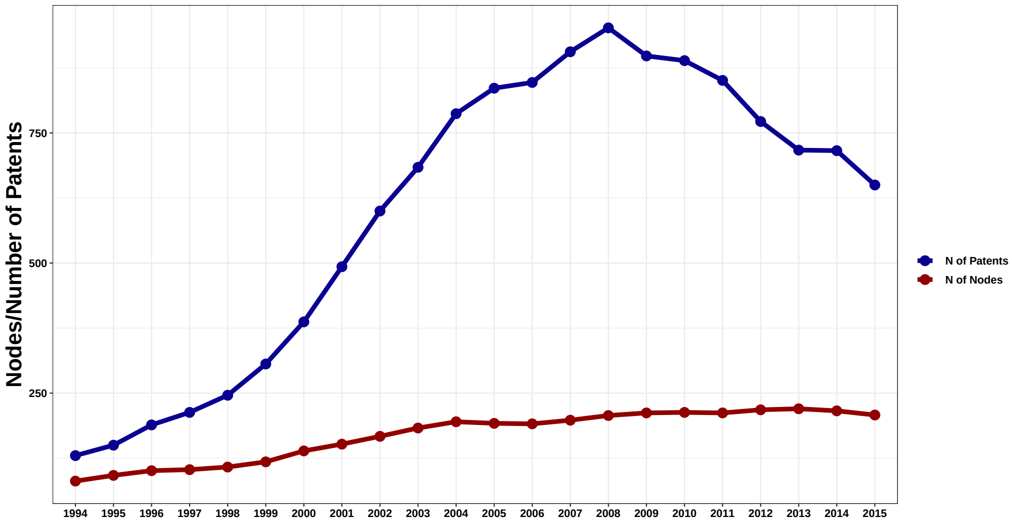


Figure 3.2: Number of Patents and Nodes in Jena KS

(Figure 3.1b), the red node does not have most connections, but it establishes a link between two otherwise separated parts of the KS.

3.4 Methodology

3.4.1 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. We use the Labour Market Region (LMR) as a regional boundary. This includes 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, Kogler, and Yan, 2017). The CPC classification is comparable to the IPC at four digits level; however, the process of re-classification from IPC to CPC allows the addition of 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, Hurtado-Albir, Angelucci, Karachalios, and Thumm, 2012). We exclude two of the Y subclasses from our analysis since they do not describe sufficiently homogeneous technologies [1].

Figure 3.2 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.

[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.

3.4.2 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 and Saviotti, 2006; Graf, 2012). The results for the co-occurrence methodology are provided in subsection 3.4.3 (with the Bridging Index) and in the appendix 3.8.

For the relatedness matrix, we use a similar approach as the revealed relatedness method explained in detail by Neffke and 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-Ochiai coefficient C_{ij} (Ochiai, 1957) to normalize the observed co-occurrences with the size difference among technologies.

$$C_{ij} = \frac{c_{ij}}{\sqrt{c_i \cdot c_j}} \tag{3.1}$$

Where c_{ij} is the simple 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 index can vary between 0 (no overlap) and 1 (i and j always appear together).

In the second step, we compare these relatedness measures for each region (C^r_{ij} during one period) with the world (C^w_{ij} world for the same period). The world relatedness helps us to understand the degree to which the regional relatedness follows global trends. Thereby, we implicitly assume that if two IPC classes are combined frequently in the world, the likelihood that they are associated within any region increases.

The differences between the region (C^r_{ij}) and the world (C^w_{ij}) are used to map the knowledge spaces, i.e., they are the edges in the regional knowledge spaces for each period. In the case of a positive difference ($C^r_{ij} - C^w_{ij} > 0$), the region combines the classes i and j more frequently than expected from observing the world relatedness.

3.4.3 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 fulfills 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, Hasan, and Saunders, 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 and Puga, 2000). The idea is that the more a technology is diversified, the more it is connected with different technologies.

$$DI_i = \frac{1}{\sum\limits_{j=1}^{n} s_{ij}^2} \tag{3.2}$$

In equation 3.2, 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 3.3.

$$BI_i = DI_i \cdot \sum_{j=1}^{n} normco_{ij} \tag{3.3}$$

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 multiplying DI with 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.

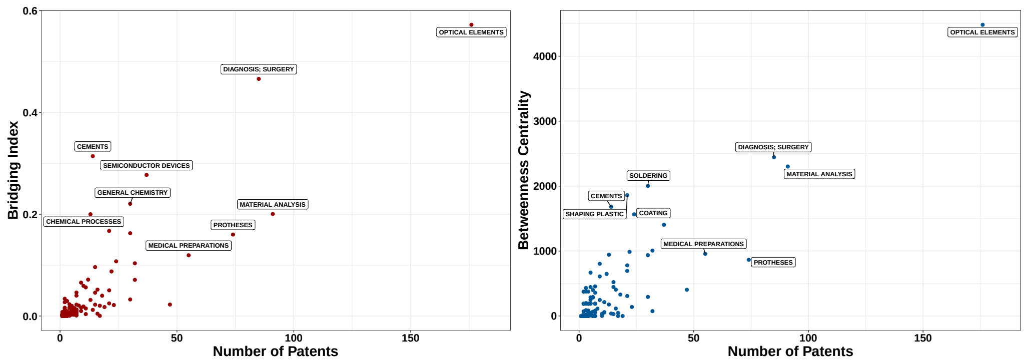
As an alternative indicator for bridging, we use the second definition of BT to understand which nodes hold a central, bridging position within the KS network. The calculation of betweenness centrality (B_i^C) for node i is provided in the following equation 3.4.

$$B_i^C = \sum_{j<k} \frac{g_{jik}}{g_{jk}}, \forall i \neq j, k \tag{3.4}$$

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 and Faust, 1994).[2] We use a weighted version of betweenness so that high relatedness edges are shorter than edges with low relatedness.

Table 3.1 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 3.3, where, for Jena in the year 2010, both measures are plotted against the number of patents. Unsurprisingly,

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



(a) Bridging Index and Number of Patents

(b) Betweenness Centrality and Number of Patents

Figure 3.3: Correlation between the bridging measures and the number of patents of each 4-digit CPC class in Jena for a representative year (2010).

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 3.1: 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

3.5 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.

3.5.1 Bridging Index (BI)

In figure 3.4, 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 appear 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, and it only loses its high position 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*.

3.5.2 Betweenness Centrality (BC)

In figure 3.5, 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 3.4). There is more turbulence when using betweenness centrality than with the BI above, so that the interpretation is less straightforward.[3]

[3] In Appendix 3.8, 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.

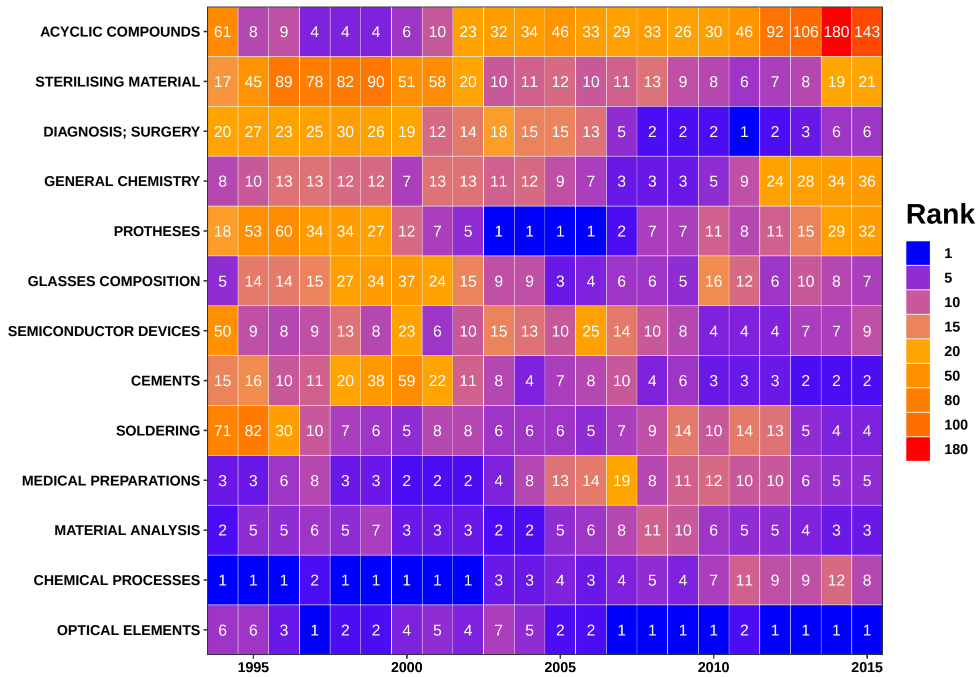


Figure 3.4: Bridging Index Ranking in Jena (1990-2015)

The two technologies identified as BTs throughout the whole period are as in figure 3.5: *Material Analysis* and *Optical Elements*. *Measuring* and *Chemical Processes* are dominant in the beginning but then lose their high 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*. 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.

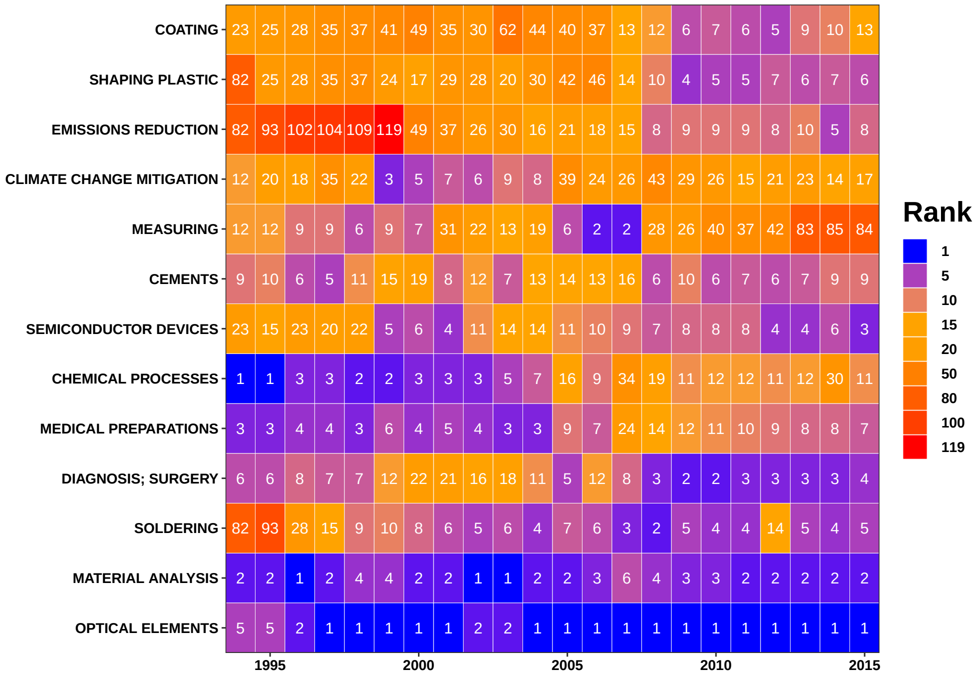


Figure 3.5: Betweenness Centrality Ranking in Jena (1990-2015)

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 and Kim, 2010; Yan and 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 3.4 and 3.5), 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.

3.6 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, 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 (3.6.2) and which technologies are increasingly well-embedded across regions (3.6.3). In addition, we exemplify the application of the RBA measure by taking a deeper look at developments within the KS of Jena (3.6.4).

3.6.1 Defining Revealed Bridging Advantage (RBA)

A widely accepted measure for assessing specialization patterns is the so-called Revealed Comparative Advantage (RCA) or, alternatively, Revealed Technological Advantage (RTA) (Hidalgo et al., 2007; Boschma et al., 2013). While the RCA is typically based on the volume of traded goods between regions, the RTA is based on the number of patents. The RTA compares shares of patents of a specific technology in a region with patent shares of the same technology at the national level. An RTA larger than 1 indicates that the region is specialized in the respective technology.

We propose the Revealed Bridging Advantage (RBA) as an index inspired by the Revealed Technological Advantage (RTA) (Soete, 1987), applied to the BC measure. In this sense, our systemic measure considers the quality of the technological interactions within the KS. It is also a comparative measure, since it is relative to the KS composition on the national level. The specialization effect will be represented in the size of the relative measure. In this sense, we can measure if a technology serves the bridging function within the local KS to a larger extent than overall in Germany. 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-digit classes that belong to the same Schmoch category, it is 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:

$$SBC_{rst} = \sum_{j \in s} BC_{rjt} \tag{3.5}$$

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:

$$RBA_{rst} = \frac{SBC_{rst} / \sum_{r=1}^{n} SBC_{rst}}{\sum_{s=1}^{m} SBC_{rst} / \sum_{r=1}^{n} \sum_{s=1}^{m} SBC_{rst}} \tag{3.6}$$

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.

To better understand how the RBA and the RTA differ from an empirical point of view, we perform a correlation analysis between these two indicators and two other variables. Table 3.2 shows the correlations between different measures on the German level. *Sum Betwenness Centrality* is exactly SBC_{rst} from equation 3.6, *RBA* is the Revealed Bridging Advantage indicator, *RTA* is the classic Revealed Technological Advantage using shares of patents at the regional and national level and *Number of Patents* is the number of patents in each region and technology.

The main encouraging result from this matrix is that the correlation between the RBA and RTA is not perfect (0.5), meaning that they are actually measuring two different concepts. Therefore, not all technologies that are regarded as important by the RTA indicator are also prominent for the

RBA indicator. In other words, not all the technologies in which a region is specialized are also the technologies that are important for the structural cohesiveness of the same region. Obviously, the two variables cannot be completely uncorrelated because if the number of patents in a specific technology increases then the probability to have combinations with others (and be in the shortest path) also increases.

Moreover, from the matrix it is evident that the RBA is less correlated (0.02) to the number of patents in each technology with respect to the RTA (0.23). This means that the RBA is less influenced by the mere number of patents that each technology in each region has, increasing its explanatory power.

Table 3.2: Correlation table among different measures

	(1)	(2)	(3)	(4)
(1) Sum Betweenness Centrality	-	0.06***	0.12***	0.61***
(2) RBA		-	0.50***	0.02***
(3) RTA			-	0.23***
(4) Number of Patents				-

Note: *p ¡ 0.1; **p ¡ 0.05; ***p ¡ 0.01

3.6.2 Regional RBA dynamics

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 (the regions included are only the ones that have at least 500 patents in the period ranging from 1990 to 2015). This should give us an indication of the performance of regions in terms of developing bridging advantages we analyse how Jena is positioned in this context.

Figure 3.6 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 fewer 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.

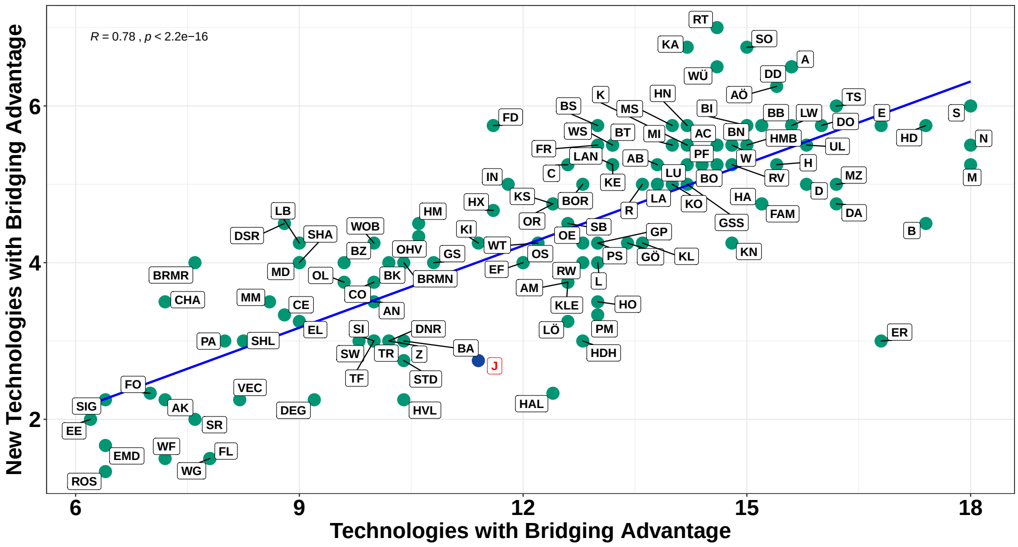


Figure 3.6: Relation between the number of technologies with an RBA > 1 at time t and the number of new technologies with an RBA > 1 at time $t + 5$ in German LMRs (1995-2015 average; 5 year intervals)

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 3.5). 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 transform 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.

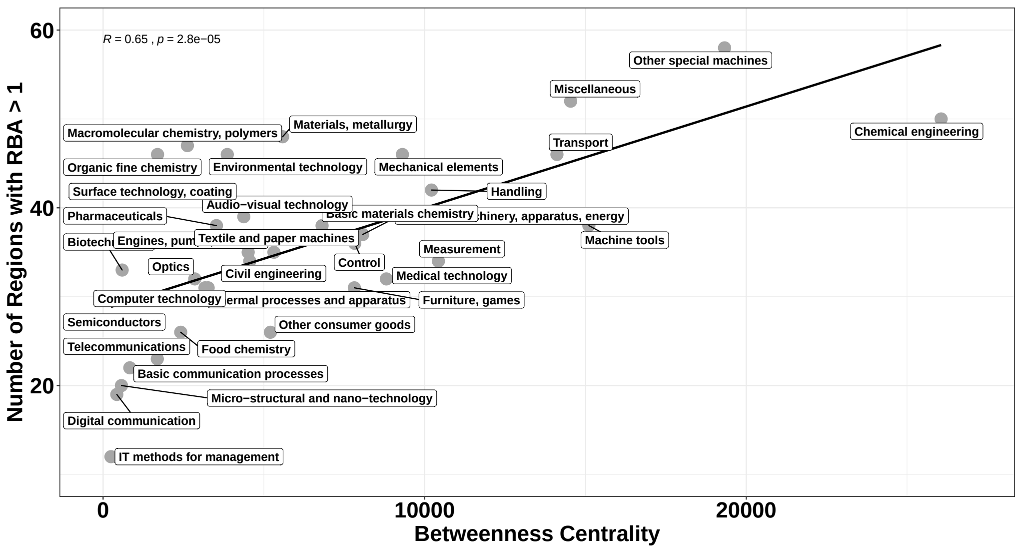
3.6.3 Technological RBA dynamics

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 3.7a and 3.7b, 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 and it takes time to observe changes in the system, 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 year 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*).

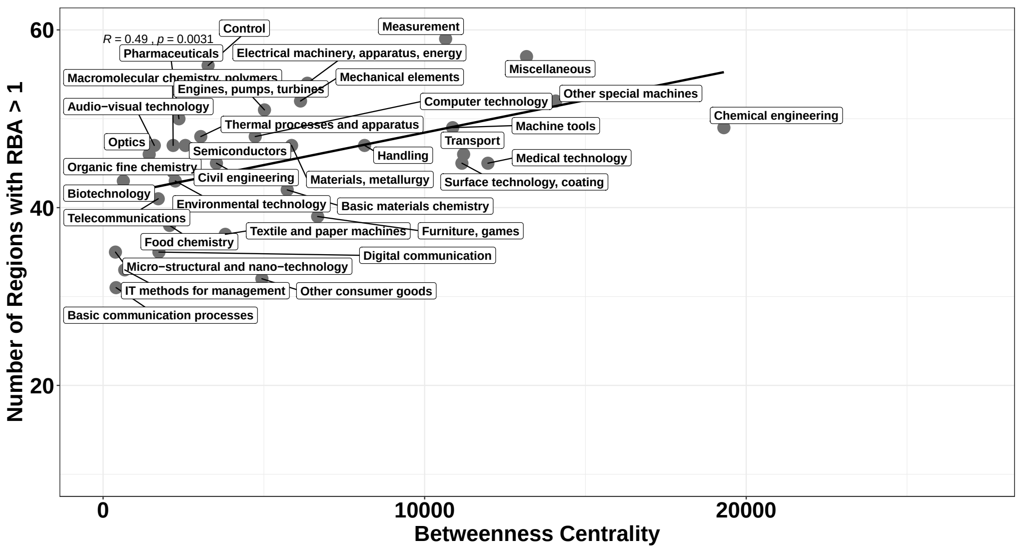
Comparing figure 3.7a and figure 3.7b, most technologies increased the number of regions with an $RBA > 1$. This means that, generally, the technologies are more diffused regionally in the German KS. Nationally, we observe a BC reduction for technologies that were particularly central in the 1995 period. 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 backgrounds in different scientific disciplines. This is reflected also on the KS with an increased possibility of interaction among different technologies (Wuchty, Jones, and Uzzi, 2007).

In figure 3.8, 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 3.7a (*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 rise in BC in 2015. 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. This type of analysis provides insights about which technologies are of increasing relevance for the German KS and which are losing 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.



(a) 1995



(b) 2015

Figure 3.7: National BC versus the number of regions with $RBA > 1$ for each technology in two different time periods

3.6.4 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

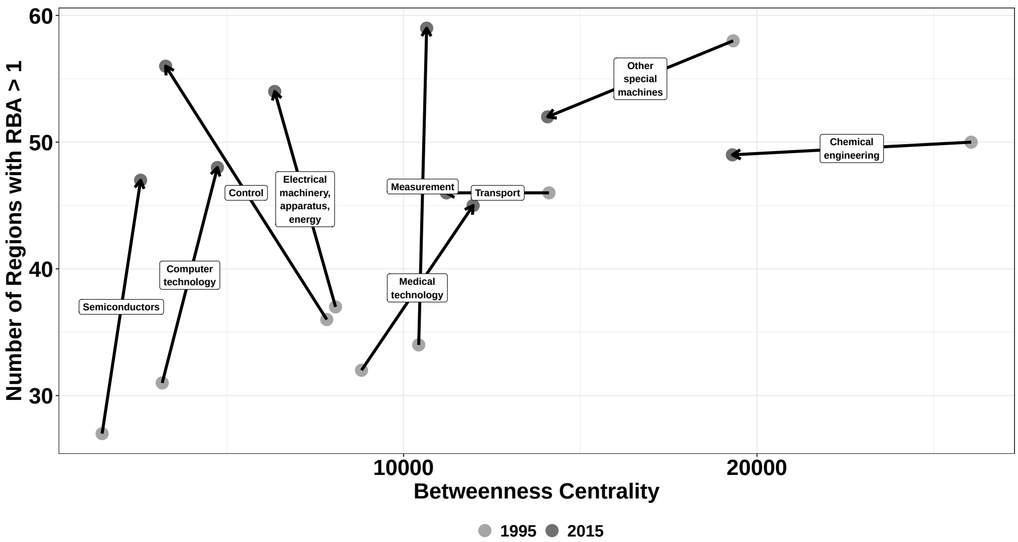


Figure 3.8: National BC versus the number of regions with $RBA > 1$ for each technology in two different time periods (comparison on selected technologies)

were driving it at the beginning of the considered period are not important in the Jena KS anymore. It also helps us to assess whether the BTs identified in the previous section are Jena specific.

In figure 3.9, 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 *Optics* 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 3.6.2 and figure 3.6). *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.

3.7 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 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 a 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.

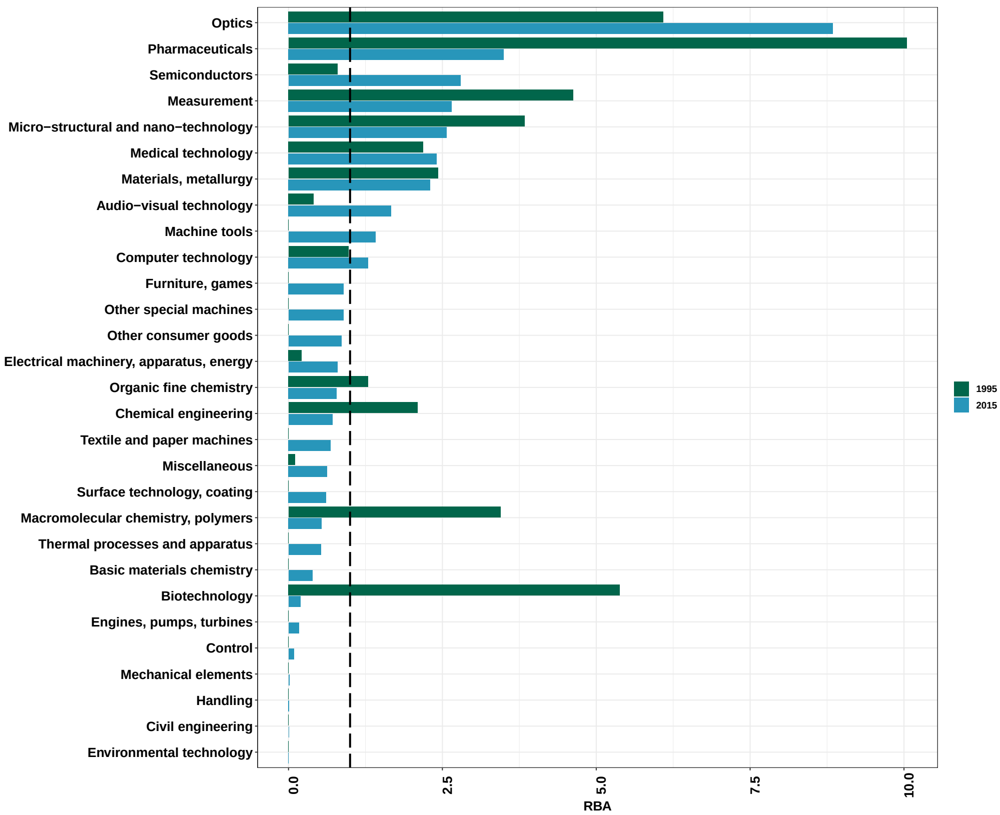


Figure 3.9: RBA comparison in two different periods of time (1995-2015)

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) and 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 an analysis of 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 has 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 and are 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 shows 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 losing 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, Dernis, and Criscuolo, 2013), it would be possible to understand if these patents are more valuable in terms of citations, for example, and if they spur the innovative activity of the area. Given the ongoing discussion about the role of public research for technology development (Graf and Henning, 2009; Graf and Menter, 2021), it could be a fruitful avenue to explore if public research is also a relevant actor in bridging technologies.

3.8 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.

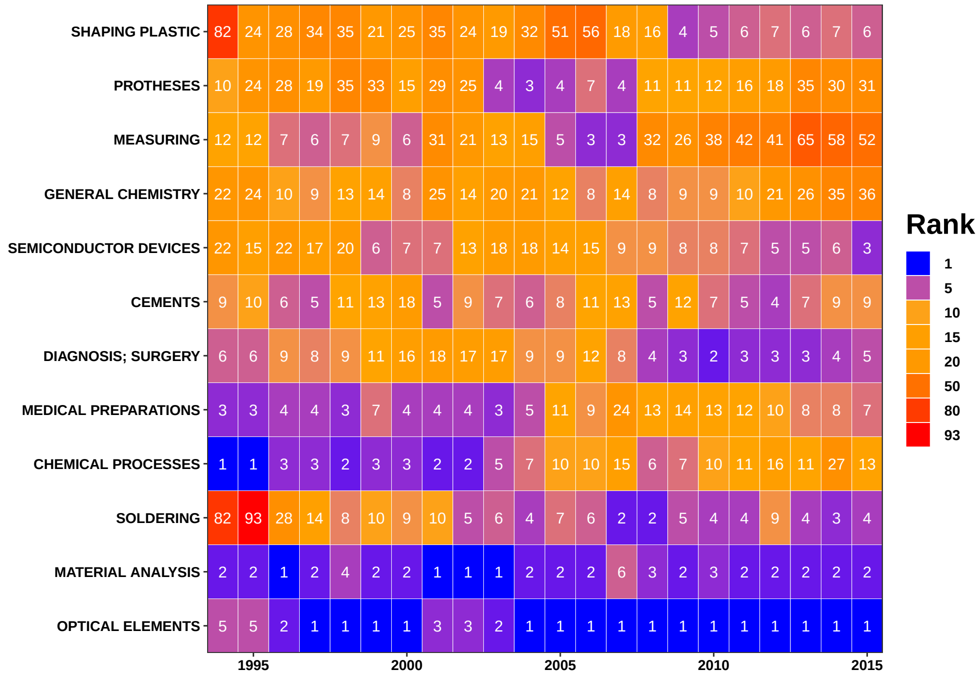


Figure 3.10: Node Betweenness Centrality on Co-occurrence matrix ranking in Jena (1990-2015)

3.9 Descriptive statistics and correlations for all German regions

Table 3.3: 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

3.10 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 had the highest presence of patents worldwide. 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 their evolution, the slight differences when passing from IPC to CPC are not taken into account.

Table 3.4: 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

3.11 LMR Abbreviations

Table 3.5: 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

Chapter 4

Policy Influence in the Knowledge Space: a Regional Application

4.1 Introduction

Cluster policies are a popular instrument of regional innovation policy, often implemented to deal with so-called systemic failures by establishing and fostering interaction between innovative agents. Despite their systemic nature, most evaluation studies focus on policy effects on individual firms, thereby treating them similar to other types of R&D subsidies. These studies typically identify positive effects on R&D inputs while results on innovation-related outputs are more mixed (Mar and Massard, 2021).

Since clusters are composed of a variety of actors and organizational types, including not only firms but also universities, research centers and research services, a focus solely on the effects on firms poses unjustifiable limitations to their analysis. In addition, policy effects on the composition and structure of relations within a cluster are often overlooked and pose a substantial challenge for cluster policy evaluation (Uyarra and Ramlogan, 2012). Because of the variety of policy targets and complex interactions of different instruments within cluster policies, several scholars call for wider and more systemic evaluations (Mar and Massard, 2021; Rothgang et al., 2021). A few recent studies tackle these shortcomings of the field and apply social network analysis (SNA) to understand how policy affects the overall structure of relationships between different actors (Giuliani et al., 2016; Töpfer et al., 2019; Graf and Broekel, 2020; N'Ghauran and Autant-Bernard, 2020). While cohesive networks have been identified as drivers of innovation-based economic development of regions (e.g. Breschi and Lenzi, 2016), these studies provide only limited evidence for positive effects of cluster policies on network cohesion.

Another important structural feature of regions which has been associated with economic development is the knowledge space (Kogler et al., 2013). The knowledge space is a network of interrelated technologies that can help us understand the structures and characteristics of regional knowledge capacities, i.e., it is a representation of the regional knowledge base. Its structure is considered important for the regional creation and accumulation of knowledge and has been used for comparing the technological structure and evolution of regional innovation systems (RIS) (Kogler et al., 2013; Boschma et al., 2014; Balland, Rigby, and Boschma, 2015). The knowledge space and the related product space shape the direction of change in innovative activities. These spaces set constraints by indicating if required competencies for the development of specific technologies are present in a region, and they create technological opportunities by revealing potential for new knowledge recombinations (Malmberg and Maskell, 1997; Sonn and Storper, 2008). As such, they are considered important determinants of economic development and growth (Hidalgo et al., 2007; Hausmann and Klinger, 2007). Given that many innovation-oriented cluster policies have a technological focus, we expect that such policies are able to shape and redirect the knowledge space of regions to open new technological pathways. However, to our knowledge, this concept has not been used to understand the effects of a cluster policy.

Within the variety of cluster policies, we relate to the innovation-oriented cluster policy which focuses its support on collaborative R&D activities within selected regions. The main goal of such policies is to increase innovativeness and competitiveness of the supported clusters, the regions where they are located or even of the national economy. The main instrument to achieve this goal is to stimulate collaborative, innovation-related activities in more or less precisely defined industries or technology fields. As such, the effects of such policies should show in the structure of the knowledge space. Supported fields of activity should increase their visibility and importance within the knowledge space by either creating or intensifying links within the field itself (along existing trajectories) or by creating links with previously unrelated fields (cross-fertilization). A greater impact on the whole economy or innovation system is to be expected when technological relations with other fields are established and enforced, indicating a broad diffusion of the technology and its applications.

In order to analyze how cluster policies shape the knowledge space, we focus on the German BioRegio contest. This program was implemented when Germany was lagging behind the United Kingdom and the United States in the development and commercialization of biotechnology (Cooke, 2001). The German federal government and local authorities started to develop initiatives to try to close this gap; one of them was the BioRegio contest (Dohse, 2000). There were 17 regions that applied for this program, and four of them won the contest. The program, whose main aim was identifying and strengthening clusters that were already performing well in biotechnology, started in 1997, and funding ended in 2005 (Dohse, 2000).

Other goals of the BioRegio contest were to increase collaboration among existing actors, to support entrepreneurial activities in the field of biotechnology and to combine biotech with other, previously unrelated technologies (Dohse, 2000; Dohse and Staehler, 2008). The latter goal is an important aspect for our analysis, since new combinations between different technological fields enable cross-fertilization effects and change the shape of the knowledge space. We look at these changes in order to evaluate the impact of the BioRegio contest on the regional knowledge space.

We track the evolution of biotech in all 17 regions during and after the policy and expect these technologies to become more central and more connected to other fields. Our results show that the BioRegio contest contributed to an increase in the importance of biotechnology in the four winning regions in terms of connectedness with other fields and importance in the knowledge space. The effect is visible after the policy ceased its funding period. Also, we find that in the post-treatment period, biotechnology in winning regions experienced higher growth than biotechnology in the non-winning regions.

We proceed as follows. In Section 4.2, we review the literature on clusters, cluster policies and knowledge spaces. We introduce the BioRegio contest in Section 4.3 and provide a descriptive analysis of changes in regional knowledge space in Section 4.4. Section 4.5 presents the econometric approach along with a description of the variables, in particular, betweenness centrality as our measure of knowledge space embeddedness of a technology. Section 4.6 presents the main results of the difference-in-differences approach and Section 4.7 concludes.

4.2 Literature Review

4.2.1 Clusters and knowledge diffusion

To understand why policy makers are so interested in clusters and why they decide to intervene and support them, we should first define the benefits associated with agglomeration externalities and the clustering concept. Marshall (1890) proposed three different types of agglomeration externalities that arise in environments with specialized industries in the same location: the accessibility to a market with high skilled workers, the availability of auxiliary and supporting activities (technological and knowledge spillovers) and the presence of companies specialized in different phases of the production chain (Martin and Sunley, 2003; Martin and Sunley, 1996).

A revived interest in clusters followed Porter (1990), who proposed a neo-Marshallian cluster concept in his work on international competitiveness. He argues that although the phenomenon of globalization should reduce the importance of local agglomerations, this is not the case. On the contrary, the competitive advantages of international markets are realized locally (Porter, 1998). This is where the proper milieu is formed, characterized by a concentration of elements necessary for creating a competitive advantage (highly specialized knowledge, institutions, competition, cooperation and customers with specific needs). Despite the popularity of Porter's view, there is no consensus on the definition of a cluster (Martin and Sunley, 2003; Duranton, 2011). As noted by Martin and Sunley (2003), the past decades saw economic geographers develop many similar concepts, such as "industrial districts" (Markusen, 1996), "network regions" and "learning regions," which results in ambiguity around the concept of clusters.

There is a broad discussion in the literature about the advantages of being located within a cluster. Several studies point out how firms benefit from the unique mix of collaboration and competition, as well as from complementary goods or technologies present in the region (Porter, 1998; 2000; Belleflamme, Picard, and Thisse, 2000). In their study on innovative activities in the UK, Baptista and Swann (1998), show that firms located in clusters (high regional employment in own sector) are more innovative. Beaudry and Breschi (2003) show that firms have tangible benefits only if other companies in the same location are innovative themselves. Audretsch and Feldman (1996), studying selected industries and states in the US, find that innovative activities tend to cluster, especially in the early stages of the industry life cycle. They provide evidence of a dispersion of innovative activities during later stages and argue that this is because of a lock-in situation where new space is necessary to develop new ideas. Delgado, Porter, and Stern (2014) show how industries thrive in strong clusters experiencing high employment and increasing in patenting activities. Furthermore, they highlight how the initial endowment (in terms of occupation and patenting activity) positively influences industry development within a region.

Research on clusters then moved beyond the Marshallian conceptualization of knowledge spillovers. One of the strongest criticisms of this view is that it is not sufficient to be located in the same geographical space to benefit from knowledge externalities for innovation. Firms inside a cluster do not equally benefit from knowledge embedded in the region; knowledge is not simply "in the air" (Giuliani and Bell, 2005). To acquire external knowledge, firms need specific characteristics (e.g., the right cognitive distance) as well as the right connections (Boschma, 2005). Therefore, researchers shifted their attention to studying the relationships among the actors within clusters to understand their innovative capacities and performance (Boschma and ter Wal, 2007). Research on clusters and regional innovation has thus been complemented by aspects of the structure and evolution of innovation networks (Koo, 2005; Cantner and Graf, 2006; Giuliani and Bell, 2005; 2008). These ideas also entered the policy realm by an increased support of collaborative activities in innovation policy (Broekel and Graf, 2012; Cantner and Vannuccini, 2018).

4.2.2 Cluster policies

Policy makers support clusters on national, regional and local levels (Kiese, 2019; Sternberg, Kiese, and Stockinger, 2010). Frequently building on Porter's cluster concept, these policies have an increase in competitiveness of the region or nation as their ultimate goal. An intermediate goal to achieve competitiveness is an increase in innovation by means of supporting R&D, collaboration and network formation to facilitate knowledge spillovers. Such innovation-oriented cluster or network policies are justified from different perspectives (see, e.g., Cantner and Vannuccini, 2018; Graf and Broekel, 2020, for more detailed discussions). First, networks are known to drive the economic and innovation performance of organizations and regions (Breschi and Lenzi, 2016; Broekel, 2012; Fornahl et al., 2011). Second, funding of collaborative R&D to support network formation is quite simple to implement in existing funding schemes (Broekel and Graf, 2012) and has been shown to lead to behavioral additionality (Wanzenböck, Scherngell, and Fischer, 2013; Lucena-Piquero and Vicente, 2019). Third, system or network failures reduce interorganizational knowledge access and exchange because of intermediation, complementarity and reciprocity problems (Cantner, Meder, and Wolf, 2011; Cantner and Vannuccini, 2018; Lucena-Piquero and Vicente, 2019).

Cluster policies are rooted in a variety of policy fields, such as science and technology policy, industrial policy and regional policy (Sternberg et al., 2010). Therefore, they come in various forms and can show a wide set of design features (Hospers and Beugelsdijk, 2002, p. 382). Cluster policies focus on actors when their goal is to provide support to specific groups of actors, such as SMEs, start-ups or science industry relations. If the aim is to support specific industries (industrial policy) or technologies with high potentials and expected impact (GPTs, climate change mitigation), theme-related characteristics are of relatively greater importance. As with innovation policy, we can distinguish between technology-specific and unspecific measures in cluster policy. Take, for example, two prominent cluster policies in Germany. The BioRegio contest was focused on promoting biotechnology (and was therefore technology-specific), whereas the subsequent Leading-Edge Cluster Competition was open to all types of technologies and industries (Rothgang et al., 2017; EFI, 2017). In both cases, clusters were selected by an independent jury who took into account the capabilities and experience of actors, their past and future interactions and the type of knowledge or technology to be created. Moreover, the program directors and the jury valued or even expected interdisciplinary approaches and visions regarding the cross-fertilization between related fields to open new technological pathways. For example, Bioinstruments Jena was selected for its innovative coupling of organic chemistry and microbiology with optics and instruments. Therefore, a combination of actors with diverse capabilities and technological backgrounds with a “optimal” level of cognitive proximity could be considered an asset.

The popularity of cluster policies attracts much research on their effects and consequences. According to Mar and Massard (2021), there is ample evidence for positive effects on R&D inputs while results on innovation-related outputs are mixed or inconclusive. Typically, such evaluation studies focus on the economic and innovative effects on single firms (Nishimura and Okamuro, 2011; Broekel, Fornahl, and Morrison, 2015; Mar and Massard, 2021) or on regional aggregates (Engel, Mitze, Patuelli, and Reinkowski, 2013). However, a cluster consists not only of firms but of a variety of actors with different characteristics, as well as the relations between them. In fact, the performance of a cluster is based on how the different actors interact and not on how the single elements perform (Andersson and Karlsson, 2006). Recently, a number of studies tried to fill this gap by applying social network methods within cluster policy evaluation (Giuliani et al., 2016; Töpfer et al., 2019; Graf and Broekel, 2020; N’Ghauran and Autant-Bernard, 2020). Some of these studies indicate that there are short-term intended effects of cluster policies on cohesion in actor networks, but they also point out limited long-term effects and partly unintended structural effects, such as an increase in network centralization (Töpfer et al., 2019; Graf and Broekel, 2020). In contrast to the actor level, we know very little about the cluster policy effects on the direction of technological development. Given that technological innovations are one of the core goals of cluster policy and that politicians strive to become more proactive in terms of the direction of innovation (Cantner and Vannuccini, 2018; Kattel and Mazzucato, 2018), we should also be more interested in effects on the technology dimension.

4.2.3 Adding the knowledge space to cluster policy evaluation

One of the possible methods to measure knowledge generation over space and time (to map the knowledge space) is to use the concept of relatedness. This method allows calculation of "proximities" between different technologies to give a sense of how knowledge in a particular area (that could be a nation, a region or a city) is connected (Kogler et al., 2013). The concept of relatedness is not new; in fact, it was already present in the innovation literature in the 1980s and 1990s, where it was used to demonstrate the relevance of knowledge spillovers (Rosenberg and Frischtak, 1983; Carlsson and Stankiewicz, 1991). In particular, Pavitt (1984) and Jaffe (1989) argue that innovation is favored by connections between different fields of knowledge. Teece et al. (1994) show how the knowledge base of a firm is linked to the portfolio of technologies it owns. Breschi et al. (2003) use patent data to understand how firms diversification into related technologies affects their performance.

Hidalgo et al. (2007) and Hausmann and Klinger (2007) were pioneers in studying the concept of relatedness using international trade data to understand the "proximity" between exported products among different countries. Their methods allow them to predict countries' future export specialization into related products based on its existing capabilities. Subsequent studies followed this approach and adapted it to the regional level (Boschma et al., 2012; Neffke et al., 2011; Quatraro, 2010; Kogler et al., 2013; Boschma et al., 2014; Balland et al., 2019). Kogler et al. (2013) analyzed the knowledge space of the US and identified systematic differences between cities in terms of knowledge space structure and evolution. For example, relatedness in small cities is higher than in large cities, and higher levels of relatedness indicate higher growth in knowledge production. Boschma et al. (2014) look into the drivers of technological evolution in US cities and find that entry of a new technology in a city is more likely if it is related to existing technologies, while the exit probability declines with increasing relatedness. However, cities with a diverse knowledge space that is proximate to technologies outside their fields of comparative advantage seems to have benefits in terms of higher resilience in phases of technological downturn or crisis (Balland et al., 2015). From these studies, it follows that an expansion of the knowledge space is easier to accomplish if it includes technological fields that are related to the region's existing competencies, thus strengthening its performance.

Despite this evidence on the relevance of the knowledge space for regional development, we know little about policy effects on the knowledge space. In particular, cluster policies, with their focus on actors with specific technological competencies, should affect the structure of the knowledge space. We expect that supported fields of activity increase their visibility and become more important within the knowledge space by either creating and/or intensifying links within the field itself (along existing trajectories) or by creating links with previously unrelated fields (cross-fertilization). In the case of BioRegio, one of the aims was to create bridges between biotech and other technologies (Dohse, 2000; Staehler, Dohse, and Cooke, 2007). Thereby, regions should increase their capabilities to create new applications and a wider diffusion of the technology. Against this background, we assess whether the policy met these expectations, and more importantly, we provide a framework that might be used for other cluster policies.

4.3 The BioRegio Contest

To analyze if cluster policies have the ability to reshape the knowledge space and change its technological trajectory, we focus on the German BioRegio contest. In the 1990s, Germany was said to be lagging behind other leading countries (such as the US or the UK) in the development of a biotechnology industry (Cooke, 2001). There were some institutional barriers that prevented the formation of a biotechnology industry in Germany. In particular, there was a low number of companies that were performing biotechnology research, a weakly developed venture capital market and governmental barriers connected to the regional support of biotechnology (Krauss and Stahlecker, 2001). Therefore, the German federal government started to develop initiatives to try to reduce the gap, with the BioRegio contest being one of them (Dohse, 2000; Kaiser and Prange, 2004; Dohse and Staehler, 2008). The main aims of this and subsequent policies was to stimulate the development of life science clusters, increase the number of biotech start-ups, enhance the performance of existing biotech firms, support the supply of venture capital and improve the acceptance of biotechnology in the population (Eickelpasch and Fritsch, 2005; Champenois, 2012). Another focal objective was to combine biotechnology with other technologies in novel ways (Dohse, 2000; Dohse and Staehler, 2008). In fact, this last aspect is an important motivation for our analysis, since the creation of new combinations between different technological fields is a driver of knowledge space evolution.

BioRegio was a competitive program, encouraging proposals from different local authorities that could meet these objectives. Submissions should highlight the core characteristics of the respective region and how the network structure could support the achievement of the set objectives (Müller, 2002; Dohse, 2000; Dohse and Staehler, 2008). The evaluation of the projects was performed by an international jury of scientists, representatives of labor unions and industry. The selection criteria for project assessment were the following (Dohse, 2000; Staehler et al., 2007):

- number and size of firms oriented to biotechnology already present in the region;
- number, characteristics and productivity of research facilities and universities in the region;
- ways in which different biotech research branches interact in the region (networking characteristics);
- supporting services (patent offices, information networks and consultancy);
- explanation of the possible strategies to convert biotechnology know-how present in the region into new products, processes and services;
- offer of help on a regional level to support biotechnology start-up activities;
- provision of financial resources through banks and public equity to economically support biotechnology firms;

- cooperation among clinical hospitals and biotech research institutes regionally;
- approval of new experiments and new facilities by the regional authorities through a smooth process.

The regional boundaries were not predefined by the application call (there was no exact indication about the composition of the consortium). Instead, local authorities could decide autonomously which regions to include in their applications (Champenois, 2012). Nevertheless, geographic proximity played a substantial role, and the core actors were all located in close vicinity (Engel et al., 2013). The regions that participated are very different in terms of population. For example, the most populated region (Berlin-Brandeburg) has a population of 6 million inhabitants, while the smallest one (Jena) has only slightly more than one hundred thousand. Some applicants are single cities, while others are larger areas which include several cities (Dohse, 2000).

Overall, 17 regions submitted proposals and three of them won the contest: Munich, Rhineland (Cologne, Aachen, Düsseldorf and Wuppertal) and the Rhine-Neckar triangle (Heidelberg, Mannheim and Ludwigshafen). A special vote was given to Jena because of its specialization in Bioinstruments and as the best proposal from an East German region (Dohse, 2000; Graf and Broekel, 2020). Funding was provided from 1997 to 2005 (Staehler et al., 2007). The three winning regions received support from the BMBF with 25 million EUR each and Jena was supported with 15 million EUR in public funds (Engel et al., 2013). Due to its success, this innovative approach towards clusters inspired other BMBF policy initiatives, such as: InnoRegio, BioProfile, Leading Edge Cluster Competition and InnoProfile (Dohse and Staehler, 2008; Eickelpasch and Fritsch, 2005; EFI, 2017).

Several studies evaluate the BioRegio contest and identify, in general, positive developments according to various indicators, such as short-term R&D activity, venture capital funding, firm births, employment growth and reputation effects (Staehler et al., 2007; Dohse and Staehler, 2008; Engel et al., 2013; Graf and Broekel, 2020). In contrast, Engel and Heneric (2008) find that BioRegio participant regions which were not successful in the contest outperform winning regions in terms of changes in the number of newly founded biotech firms during the funding phase. The few studies that test for long-term effects of BioRegio on innovation activity or innovation networks find mixed or inconclusive evidence (Engel et al., 2013; Graf and Broekel, 2020). One of the reasons for the difficulty of identifying long-term effects is that subsequent biotech-related programs, such as BioProfile on the national level, or funding by the EU and regional governments, had effects on a broader set of regions, which might be included in the control groups of the respective studies. Given that we do not have access to funding data for all levels of government, the present study suffers from the same limitation. However, if untreated regions benefit from such unobserved policies, that should lead to an underestimation of the observed policy effects.

4.4 Biotechnology in Regional Knowledge Spaces

4.4.1 Patents and regions

We use PATSTAT (Autumn 2017) as our primary source to detect innovative activities. The International Patent Classification (IPC) on the 4 digit level (IPC4) is used to distinguish between the different technologies. We adopt the OECD standard classification of biotechnology (Van Beuzekom and Arundel, 2009) to identify IPC4 classes as biotechnology[1].

Since patents are associated with different technological domains, they have proven to be a valuable source of information in capability-based research (Breschi et al., 2003; Kogler et al., 2013; Boschma et al., 2014; Balland et al., 2019; Whittle and Kogler, 2019). Their documentation is highly standardized so that they allow for dynamic analyses over long periods on various levels of aggregation. However, patents also have several well-known limitations (see Griliches, 1990, for an overview). Patent analyses are limited to inventions that can be patented so that they miss many non-patentable inventions, in particular in industries with a lower propensity to patent, such as software

[1]At the IPC 4 digit level, these are A01H, A61K, C02F, C07G, C07K, C12M, C12N, C12P, C12Q, C12S and G01N.

or services. Besides, our analysis relies on the patent classification system, and we assume that patents in the same IPC class are similar to each other but different from those in other classes. Since this classification is done by the patent offices for other reasons than this type of analysis, this might not hold true.

For the geographical boundaries of knowledge spaces, we assign each patent to a region if at least one inventor resides in that area (Cantner and Graf, 2006; Toth, Elekes, Whittle, Lee, and Kogler, 2022). The inventor-based approach is used because large companies or research institutes with many locations tend to file patents at their headquarters, which is not necessarily where the invention originates (Graf, 2017).

We consider Labor Market Regions (LMRs) for the regional boundaries. LMRs are aggregates of NUTS3 regions which are designed to account for commuting patterns. By choosing LMRs rather than NUTS3 regions, we better capture patents by inventors who reside in suburbs or rural areas and commute to their workplace in larger cities. There are 141 LMRs in Germany which comprise of cities with their surrounding areas. Our unit of observation are those LMRs where at least one city that won the BioRegio contest is located.

Figure 4.1 shows a map of Germany with the 17 regions that participated in the BioRegio contest. We distinguish between the four “winner” regions that were successful and received grants and 13 “non-winners” that did not proceed to the funding stage (Dohse, 2000). Since some applications were from networks of cities, LMRs do not always correspond to the areas affected by BioRegio. In those cases, we aggregated smaller LMRs into larger areas.

4.4.2 Mapping the knowledge space

To map the knowledge space, we consider patent applications from 1986 to 2014 in the winning and non-winning regions. This permits us to have enough time before and after the policy was running to assess its impact. To account for fluctuations of patent applications, we follow Boschma et al. (2014) and use five-year moving windows. For example, 1990 refers to the five-year period 1986 until 1990 and includes all patent applications filed

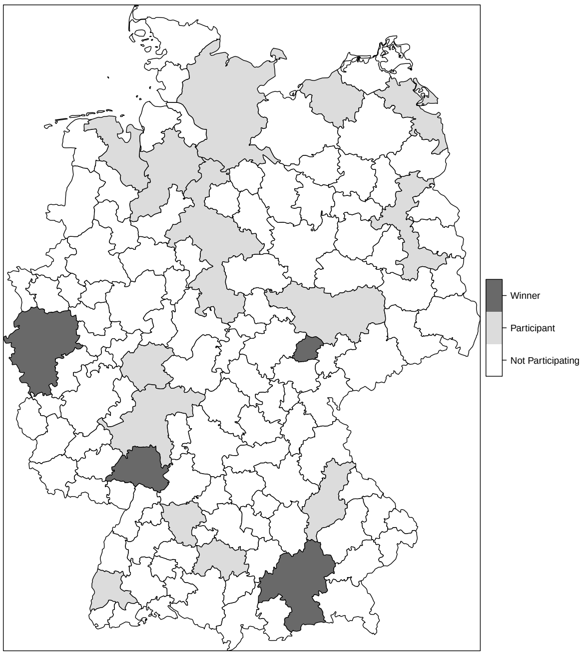


Figure 4.1: BioRegio Participants and Winners

during those years. This choice is motivated by the turbulence observed when using shorter periods, e.g., one year, especially in smaller regions. The nodes of the network are the IPC4 classes, while the edges based on the co-occurrence of IPC4 classes on patent applications, weighted according to their relatedness.

For measuring relatedness (the "proximities" among the different technologies present in the same space at the same time), we follow Basilico and Graf (2020) who use a two-step approach. In the first step, we calculate a co-occurrence matrix and assume that the more patents are assigned to two classes, the higher is their relatedness. To take into account that co-occurrences between highly frequented patent classes are more likely, we standardize co-occurrences and calculate relatedness between all pairs of IPC classes by using the Otsuka-Ochiai coefficient C_{ij} (Ochiai, 1957):

$$C_{ij} = \frac{c_{ij}}{\sqrt{c_i \cdot c_j}} \tag{4.1}$$

Where c_{ij} is the simple 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 index can vary between 0 (no overlap) and 1 (i and j always appear together).

In the second step, we compare these relatedness measures for each region (C^r_{ij} during one period) with the world (C^w_{ij} world for the same period). The world relatedness helps us to understand the degree to which the regional relatedness follows global trends. Thereby, we implicitly assume that if two IPC classes are combined frequently in the world, the likelihood that they are associated within any region increases.

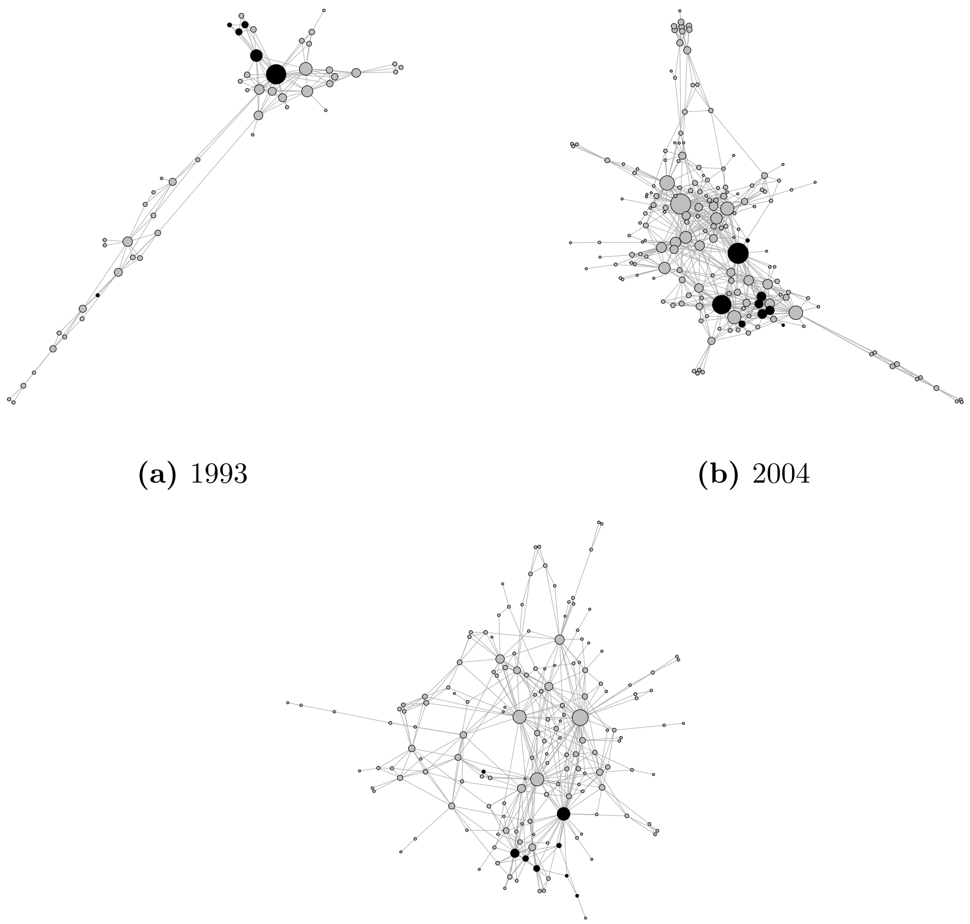
The differences between the region (C^r_{ij}) and the world (C^w_{ij}) are used to map the knowledge spaces, i.e., they are the edges in the regional knowledge spaces for each period. In the case of a positive difference ($C^r_{ij} - C^w_{ij} > 0$), the region combines the classes i and j more frequently than expected from observing the world relatedness.

4.4.3 Relational embeddedness of biotechnology

To illustrate the evolution of the knowledge space in a BioRegio winner region, figure 4.2 shows the main components of Jena before, during and after the funding period. The black nodes are IPC4 classes identified as biotechnologies by the OECD. In general, the knowledge space of Jena increased in size over time, incorporating new technological sources. Biotechnology classes became central and well-embedded during the funding period. Afterwards, they maintained some connections with other classes of the knowledge space.

In the following, we provide descriptive statistics on the development of the number of connections in the regions that won the BioRegio contest. The most simple and straightforward way to measure embeddedness of biotech classes in the knowledge space is to take a purely relational view by calculating degree centrality[2]. Degree centrality of technology i is calculated by taking the sum of its relations with other technologies in the knowledge space of a specific region r in one period j (Freeman, 1978; Graf, 2017). We expect the biotech classes to interact more intensely and with other technologies in the knowledge space during and after the funding period.

[2]Structural embeddedness, as measured by betweenness centrality, is addressed in section 4.5.



(a) 1993 **(b)** 2004

(c) 2010

Figure 4.2: Main components of the Jena knowledge space before, during and after the BioRegio program. Node size is proportional to degree centrality with biotechnology IPC4 classes in black.

To give a first impression, figure 4.3 shows the aggregate degree centrality for biotech classes in the four winning regions over time. To aggregate, we take the sum of the degree centralities calculated for each IPC4 class in biotech. The number of interactions with other classes increases during the funding period (1997-2005) and reaches its peak by the end of it in all winning regions. After funding ceases, there is a sharp decline of interactions, reaching levels below the end of the pre-funding period. While this supports our expectation of biotechnological classes becoming more embedded in the knowledge space of winning regions during the funding period, it contradicts our expectations for the post-funding phase.

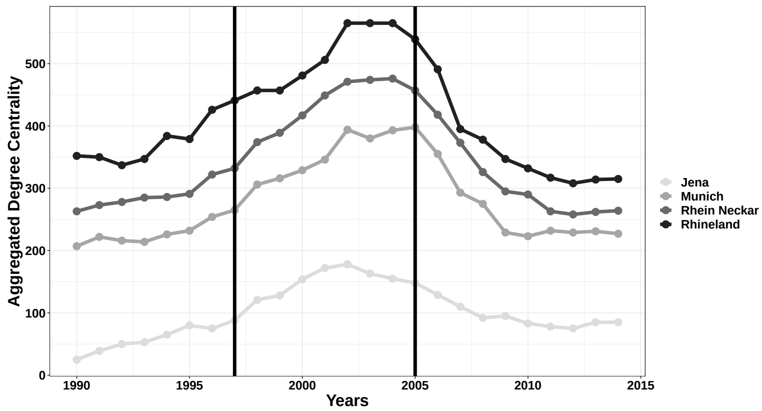


Figure 4.3: Aggregated degree centrality for biotech IPC4 classes in winning regions

For a more fine-grained analysis, we take a closer look at the newly formed linkages in the knowledge space. In order to aggregate not only the IPC4 classes belonging to the field of biotechnology but also all other fields, we use the classification by Schmoch (2008). In this classification, the IPC classes are grouped into 35 more broadly defined technology fields. In this way, we can count the number of IPC4 links established (or dissolved) between biotechnology and other fields. Figure 4.4 shows the number of new connections between biotech and the respective fields for each region during and post-funding (the technologies are ordered according to decreasing new connections during the funding period). New combinations are co-occurences between IPC4 classes that have not been combined previously in the respective region. The combinations with biotechnology classes in the pre-funding period are taken as reference to calculate the new edges created during the funding period. Regarding the post-funding period, both previous periods are taken together as a reference.

In line with our previous observation (figure 4.3), in all winning regions, most new combinations are established during the funding period. The variety of the technological classes combined with biotechnology in the four winning regions is wide. In Jena during the funding period, biotechnology establishes new connections mostly with *Organic fine chemistry* (14), *Medical technology* (13) and *Chemical engineering* (23). To observe *Medical technology* to be increasingly related with biotechnology is consistent with the focus of the projects in Jena on “Bioinstruments”. After funding, the classes with

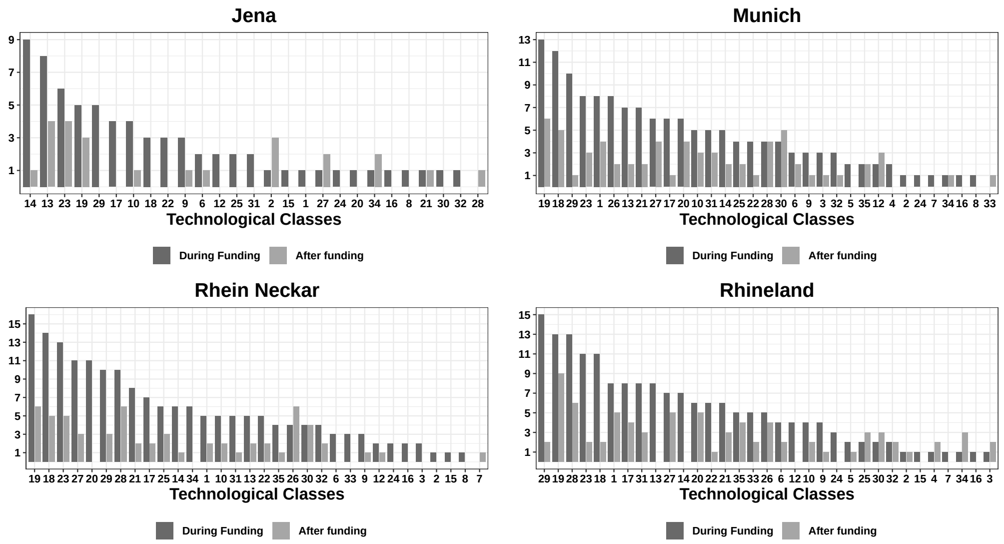


Figure 4.4: Number and type of new combinations with biotechnological classes created during and after BioRegio

most new combinations with biotechnology in Jena are *Medical technology* (13), *Chemical engineering* (23), *Basic Materials, chemistry* (19) and *Audio-visual technology* (2).

In Munich, during the funding period, biotechnology is mostly combined with *Basic Materials, chemistry* (19), *Food chemistry* (18) and *Other special machines* (29). While in the post-funding period the classes mostly combined with biotechnology are *Basic Materials, chemistry* (19), *Food chemistry* (18) and *Thermal processes and apparatus* (30).

The region Rhein Neckar during the funding period creates the highest number of edges with biotechnology in *Basic Materials, chemistry* (19), *Food chemistry* (18) and *Chemical engineering* (23). Whereas in the post-funding period, biotechnology is combined mostly with *Textile and paper machines* (28), *Machine tools* (26) and *Basic Materials, chemistry* (19).

Rhineland combines biotechnology in the period during the funding mostly with *Other special machines* (29), *Basic Materials, chemistry* (19) and *Textile and paper machines* (28). In the post-funding period the classes are *Basic Materials, chemistry* (19), *Textile and paper machines* (28), *Electrical machinery, apparatus, energy* (1), *Engines, pumps, turbines* (27) and *Materials, metallurgy* (20).

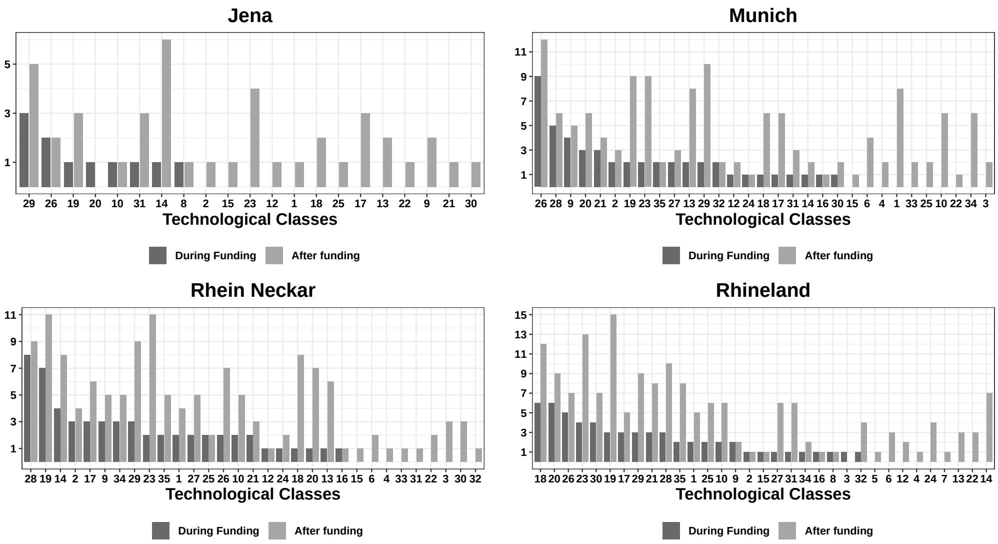


Figure 4.5: Number and type of combinations with biotechnological classes dissolved during and after BioRegio

Figure 4.5 shows the technological classes that lost connections with biotechnology in the winning regions. Since there are 11 IPC4 classes in biotechnology according to the OECD classification, it might happen that some biotech classes show new combinations while others are less connected compared to the previous period. In general, as already confirmed by figures 4.3 and 4.4, the number of interactions decreases in the post-funding period. Therefore, we observe an increase in combinations that do not exist anymore in the knowledge space of all winning regions. Another interesting result is that the technological classes that scored high in figure 4.4 during funding also score high in the period after funding, meaning that most of the new combinations created during BioRegio were not maintained after funding. This suggests that the effect on the structure of the regional knowledge space is limited to a short time span (at least in terms of the number of interactions with other technologies).

Figure 4.6 shows the number of classes in each technological field which were connected with a biotech class during the funding period but not anymore afterwards. It is interesting to observe that the classes with the highest numbers here are also the ones that established the highest number of connections in the considered regions (figure 4.4). As such, most of the edges established during the funding period disappeared afterwards. Apparently,

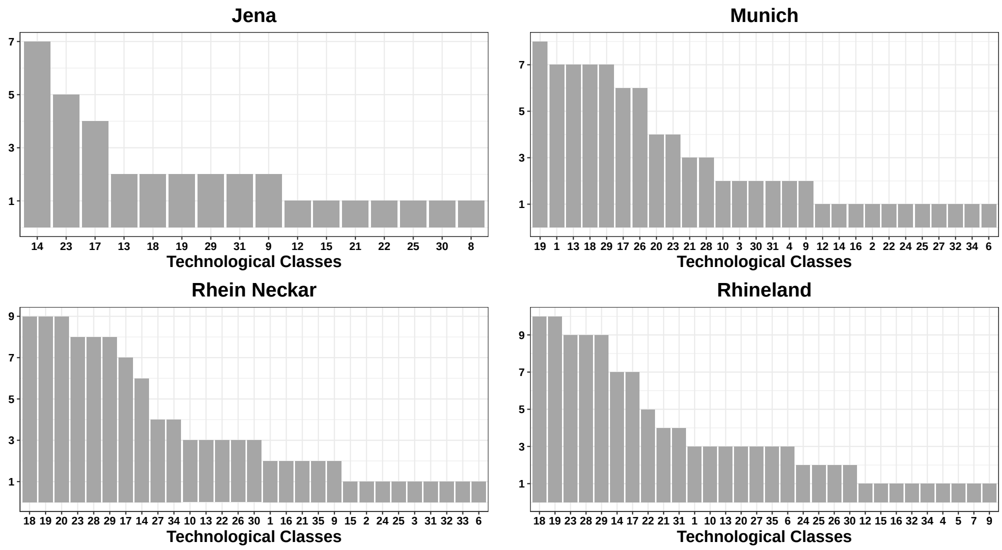


Figure 4.6: Number and type of combinations with biotechnological classes that are abandoned after the time when BioRegio was running

these connections were not maintained over time and in terms of creating new interactions in the knowledge space so that BioRegio had only a short term effect.

For example, in Jena the classes *Organic Fine Chemistry* (14), *Chemical Engineering* (23) and *Macromolecular chemistry, polymers* (17) were among the classes with the highest number of new interactions with biotech classes during the funding period but lost many of these in the post funding period. Similar patterns can be observed in the other regions as well. For Munich it involves the classes *Basic materials chemistry* (19), *Electrical machinery, apparatus, energy* (1), *Medical Technology* (13), *Food chemistry* (18) and *Other special machines* (29). For Rhein Neckar it involves the classes 18, 19, *Materials, metallurgy* (20), 23, *Textile and paper machines* (28) and 29. Finally, for Rhineland it involves classes 18, 19, 23, 28 and 29. However, there are also exceptions, such as *Medical technology* (13) in Jena, which lost almost none of its new combinations. Since this is a fundamental class to be combined with biotech classes in Jena's proposal on “Bioinstruments”, this suggests that the program had lasting effects in selected areas of the knowledge space.

4.5 Econometric Approach

4.5.1 Structural embeddedness: betweenness centrality

Complementing the descriptive analysis of the previous section, we assess the impact of BioRegio on the embeddedness of biotechnology in the knowledge spaces of regions with an econometric approach. We measure embeddedness with the betweenness centrality (BC) of each IPC4 class in the regional knowledge space. In contrast to degree centrality, which only considers the direct linkages, this network based statistic captures the bridging function of a technology by considering node positions in relation to all other nodes (Basilico and Graf, 2020). Because of its ability to capture the structural embeddedness, we use it as the dependent variable in the subsequently discussed difference in differences (DiD) approach.

Betweenness centrality measures the number of times that a node is in the shortest path between two other nodes in the knowledge space. Thereby, it captures the importance of a node for the overall connectedness of the network. A node with a high intensity relation to only one other node could score high on degree centrality even though it is unconnected to the rest of the network (Basilico and Graf, 2020). Betweenness centrality takes all indirect relations into account and if a node with high betweenness disappears, the knowledge space would be less connected. We therefore consider it more meaningful in the context of this analysis. Betweenness centrality of node i is defined by:

$$B_i^C = \sum_{j<k} \frac{g_{jik}}{g_{jk}}, \forall i \neq j, k \tag{4.2}$$

With i, j, 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 and Faust, 1994)[3]. We use a weighted version of betweenness so that edges with high relatedness are shorter than edges with low relatedness

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

(Basilico and Graf, 2020). Since we are interested in nodes that are important for the regional knowledge space, we only included the ones that have at least a score of 1, meaning that they are at least once on the shortest path between two other nodes.

For the econometric analysis, we take the logarithm of betweenness centrality since the raw measure is highly skewed to the right (meaning there are many nodes with low betweenness and few with high so that the mean is shifted to the right of the distribution).

4.5.2 Estimation strategy

The difference-in-differences (DiD) approach is widely used in the literature to assess the impact of the introduction of a policy on some performance indicators. Our approach is based on two different regression models. In the first one, we assume that biotech was treated by the policy while other technologies have not, i.e., we assess if biotechnology became more embedded in the knowledge space of the winning regions relative to other fields. In this case, we compare betweenness among the biotech IPC4 classes with all non-biotech IPC4 classes. This analysis is performed only among the winning regions. The linear model is the following (the time index is dropped for readability):

$$\log B^C_{i,r \in W} = \beta_0 + \beta_1 Time + \beta_2 Bio_{i,r} + \beta_3 (Time \times Bio_{i,r}) + \gamma_i + \delta_r + \mu \quad (4.3)$$

where $\log B^C_{i,r \in W}$ is the natural logarithm of betweenness centrality calculated for each IPC4 class (i) in all winning regions ($r \in W$), $Time$ is a dummy variable that takes value zero in the pre-treatment period (1990-1996) and value 1 in the post-treatment period (two different regressions for the time during and after BioRegio), Bio takes the value zero if the IPC4 class is not identified as biotechnology while it takes value one if it is, γ and δ are the control variables on the technology and regional level and μ represents the residuals.

In the second model, we assume that the policy treatment took place on the level of the region. Therefore, we compare betweenness of biotechnology classes within winning regions with betweenness in non-winning regions. With this regression, it is possible to understand if any trend of increased embeddedness of biotechnology identified by the model 1 is also present in other regions. If this should be the case, BioRegio would not have affected the transformation of the knowledge space of the winning regions, but there is rather a more general trend of higher bridging of biotechnology. The second model is the following:

$$\log B^C_{i \in B,r} = \beta_0 + \beta_1 Time + \beta_2 Winning_{i,r} + \beta_3 (Time \times Winning_{i,r}) + \gamma_i + \delta_r + \mu \tag{4.4}$$

where $\log B^C_{i \in B,r}$ is the natural logarithm of betweeennes centrality calculated only on the IPC4 classes identified as biotechnology ($i \in B$) in all regions (r), $Time$ is a dummy variable that distinguishes between the pre-treatment period (before BioRegio) and the post-treatment period (for the time during and after BioRegio was running), $Winning$ is a dummy variable which is zero IPC4 classes in the non-winning regions and one for those that won the competition, γ and δ are controls and μ are the residuals.

In both models, a treatment effect is observed by the coefficient of the interaction term. By differentiating between policy effects during and after funding, we capture four different effects: biotech compared to non-biotech within winning regions and biotech in winning as compared to non-winning regions, each in the short and in the long run. As noted above, our dependent variable is calculated on a knowledge space based on patent applications during a five-year period. By using moving windows for smoothing, our approach might not be best suited to identify immediate policy effects. However, given the nature of the knowledge space and the policy, we think that this a more conservative and therefore appropriate approach.

Using patent data as described in section 4.4.1, we generate several variables for the whole period (1990-2014) at the level of the single IPC4 class in each region. Table 4.1 contains all variables used for the regressions along with short descriptions. Tables 4.2 and 4.3 present descriptive statistics of the subsets of these variables used in the respective regressions. Correlations are presented in tables 4.8 and 4.9 in appendix 4.8.

4.5.3 Control variables

We control for several variables that might affect the position of a technology within the knowledge space. The first one is the log of the number of patents in an IPC4 class in one region in a specific period (*Log patents*). This variable is used to control for potentially disturbing effects of IPC4 classes with high patenting activity on the betweenness measure. Since there is a positive correlation between betweenness and the number of patents (0.59 in table 4.8 and 0.47 in table 4.9), the possibility that a node with more patents is central in the knowledge space is higher, but we are interested in the structural embeddedness induced by the policy beyond the size effect.

Avg Team Size measures the average number of inventors in each IPC4 class. For each patent, we calculate the number of inventors and take the average for each IPC4 class. There is a constant, general increase in the division of labor, which shows in more and larger teams in science and research (Wuchty et al., 2007). This trend might affect the number of interactions between different technologies since, with increasing the team size, there is more interaction among people with potentially different backgrounds. This could impact the structure of the knowledge space, with an increased number of interactions between different technological fields due only to a physiological increase in the team size and not due to the BioRegio program itself.

The third control variable is a dummy variable that distinguishes between regions located in East and West Germany (*East*). It takes value 1 for all observations from the East and 0 otherwise. This is important since, especially in the period after reunification, there was a big difference between patenting activities in the Eastern and Western part of Germany. West Germany had a higher research intensity and patented more than the East, and even though there are some high-patenting regions in the East, the process of catching-up is still ongoing. Since we cover the period right after reunification (1990-1996) as our pre-treatment period, we have to control for these structural differences.

The *Neighbour* dummy is one for all observations from non-winning regions that are neighbors of regions that won the contest. The regions that won the contest could have influenced indirectly other neighboring areas in their biotech patent production. Because of such spillovers, we should consider the

Table 4.1: Variables used in the regressions

Variable Name	Description	Regressions
	Dependent Variable	
Log Betweenness Centrality	Betweenness centrality logarithm measured on each node in the regional technological space	Both
	Independent Variables	
Time During BioRegio	Dummy variable that takes value one when the year is between 1997 and 2005	Both
Time After BioRegio	Dummy variable that takes value one when the year is between 2006 and 2014	Both
BioTech	Dummy variable that takes value one when the IPC class is a biotechnology according to OECD classification	First
Winning region	Dummy variable that takes value one when the node is from a winning region	Second
Interaction Term During BioRegio	Interaction term used for the DiD approach, takes value one only for the treatment group in the period between 1997 and 2005	Both
Interaction Term After BioRegio	Interaction term used for the DiD approach, takes value one only for the treatment group in the period between 2006 and 2015	Both
	Control Variables	
Log Number of Patents	Logarithm of the number of patents for each IPC class	Both
Avg Team Size	Average team size calculated for each IPC class	Both
East	Dummy variable that takes value one when the node is from a region in the former German Democratic Republic (GDR)	Both
Neighbor	Dummy variable that takes value one when the node is from a region sharing a common border with a winning cluster	Second

possibility that an increasing betweenness centrality in one of the non-winning regions is due to funding in a neighboring area. In the literature, there is evidence that when a cluster is supported by a policy, then automatically the neighbors also indirectly increase the number of their relationships within the cluster (Delgado et al., 2014). This is mainly evidenced in the inventor/applicant clusters, but if there are more relationships and more patents on this level, then the technological space might also be influenced. For the nature of this variable, it is only used in model 2 where non-winning regions are present.

Table 4.2: Descriptive statistics for model 1 (table 4.5)

Variable Name	N	Mean	SD	Min	Max
	Dependent Variable				
Log Betweenness Centrality	28302	5.226	1.728	0.000	9.292
	Independent Variables				
Time During BioRegio	28302	0.378	0.485	0.000	1.000
Time After BioRegio	28302	0.374	0.484	0.000	1.000
BioTech	28302	0.028	0.164	0.000	1.000
	Control Variables				
Log Number of Patents	28302	2.810	1.284	0.000	7.336
East	28302	0.055	0.227	0.000	1.000
Avg Team Size	28302	1.693	0.617	1.000	9.167

Table 4.3: Descriptive statistics for model 2 (table 4.7)

Variable.Name	N	Mean	SD	Min	Max
	Dependent Variable				
Log Betweenness Centrality	2872	5.765	2.020	0.000	9.292
	Independent Variables				
Time During BioRegio	2872	0.380	0.485	0.000	1.000
Time After BioRegio	2872	0.365	0.482	0.000	1.000
Winning region	2872	0.273	0.446	0.000	1.000
	Control Variables				
Log Number of Patents	2872	3.698	1.510	0.000	7.602
East	2872	0.210	0.407	0.000	1.000
Neighbor	2872	0.191	0.393	0.000	1.000
Avg Team Size	2872	1.894	0.551	1.000	5.200

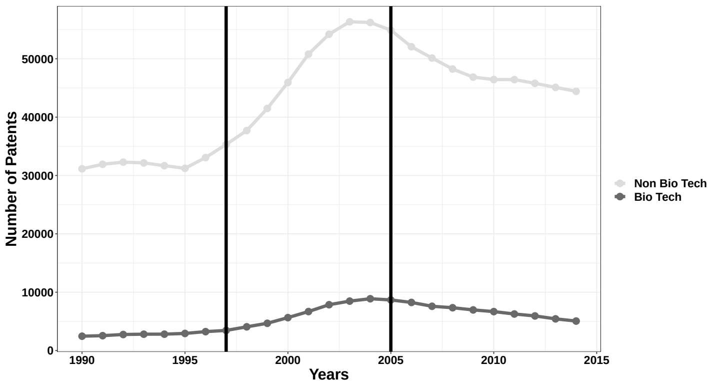


Figure 4.7: Number of patents (model 1 (table 4.5) for Biotech (treatment) and non-biotech (control) IPC4 classes)

4.6 Results

4.6.1 Biotechnology compared to other technologies in winning regions

Figure 4.7 shows the total number of patents in the winner regions for each of the two groups considered as treatment (biotech IPC4 classes) and control (non-biotech IPC4 classes) groups in model 1 (table 4.5). It becomes apparent that both groups experienced an increase in the number of patents during the period when BioRegio was running. In the period after BioRegio, the number of filed patents declined for both groups. However, as pointed out above, to assess the policy effects on the knowledge space it is not sufficient to simply count the number of patents. It is not the amount of the innovative activity that determines the quality of a system. Instead, it is the number and the quality of interactions among the elements of this network. Therefore, it is necessary to use measures able to evaluate the changes on the structure of the knowledge space over time.

Table 4.4 shows a mean comparison of the log betweenness centrality for the two considered groups. In addition to the means of both groups, their difference, the significance and the standard errors are shown for each considered year. It is important to note that the hypothesis of parallel trends in the pre-treatment period (fundamental condition for the DiD approach) cannot be rejected. The difference between both groups in the

Table 4.4: Mean comparison of log betweenness centrality. Treatment and control groups as in model 1 (table 4.5)

Year	Non-Biotech Mean	Biotech Mean	Difference	SE
		Pre-Treatment		
1990	5.344	5.341	-0.003	0.443
1991	5.277	5.253	-0.025	0.444
1992	5.293	5.252	-0.042	0.404
1993	5.281	5.394	0.114	0.415
1994	5.299	5.291	-0.008	0.424
1995	5.347	5.393	0.046	0.429
1996	5.320	5.081	-0.239	0.479
		During-Treatment		
1997	5.263	5.330	0.067	0.442
1998	5.248	5.453	0.205	0.340
1999	5.253	5.406	0.153	0.344
2000	5.104	5.528	0.424	0.325
2001	5.092	5.447	0.355	0.376
2002	5.047	5.378	0.331	0.382
2003	5.030	5.383	0.353	0.400
2004	5.053	5.531	0.478	0.406
2005	5.084	5.412	0.328	0.390
		Post-Treatment		
2006	5.179	5.718	0.54	0.368
2007	5.229	5.697	0.468	0.425
2008	5.227	5.822	0.595	0.415
2009	5.269	5.988	0.719.	0.379
2010	5.289	5.931	0.642.	0.377
2011	5.259	5.991	0.732*	0.328
2012	5.269	5.871	0.601.	0.330
2013	5.218	6.174	0.955**	0.348
2014	5.277	6.229	0.952*	0.381

period before funding is marginal and not significant. However, a difference between the two groups starts to develop while BioRegio was running. The gap widens by the end of the considered period when it also becomes statistically significant.

Figure 4.8 shows the predicted values of log betweenness for treatment and control groups from the base-line model (considering only $\log B^C_{i,r\in W}$ and $\beta_2 Bio_{i,r}$) for model 1. The graph adds support to the hypothesis of parallel trends in the pre-treatment period observed in table 4.4. The visual representation helps us to understand how the predicted values change over time, and we observe an increasing difference between the dashed (treatment

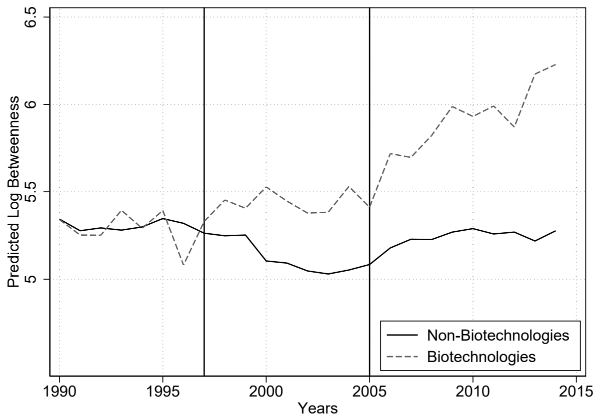


Figure 4.8: Fitted trends comparison for model 1

group) and the solid (control group) lines. This indicates that BioRegio had a positive influence on the embeddedness of biotechnological classes in the knowledge spaces of the winning regions. In the post-treatment period, both curves show an increase in betweenness centrality. Since this might be related to the simultaneous decrease in the total number of patents, it is necessary to control for the number of patents in the subsequent regressions.

To test the influence of BioRegio on biotechnology embeddedness, we performed a classical DiD regression, i.e., a simple OLS with clustered standard errors over time with regional fixed effects (table 4.5). The first column (model 1a) shows the results for the period in which the policy was running. Here, the interaction term is negative and significant. This indicates that the policy in this time frame was not effective in better connecting biotechnology with other classes in the winning regions. As such, it did not contribute to an increased connectedness and density in the knowledge spaces beyond its positive impact on the number of patents in biotechnology.

In model 1b, we test if there are effects in the period after BioRegio funding. Here, the interaction term becomes positive and significant. This means that the biotechnology classes become more important and more connected in the knowledge space of the winning regions compared to other technologies in the post-treatment period[4]. One possible interpretation of these results

[4] As explained by Basilico and Graf (2020) the usage of a different methodology to map the knowledge space can change the results when calculating centrality measures. Using a simple co-occurrence matrix instead of a relatedness matrix, the results on the calculated betweenness centrality do not vary.

is that during the initial stages of the program, research was focused on incremental and refined what was already known. Later in the funding period, research shifted and started to connect biotechnology with other, distant fields. Due to the time lag between funding and patentable output, which might also differ between incremental and more radical innovations, an exact attribution of these changes is difficult. Nevertheless, our findings indicate that BioRegio was a trigger to allow exploration of different capabilities that were not accessible inside the regions before.

Table 4.5: Comparing structural embeddedness between biotech and non-biotech classes in winning regions (DiD regression, robust standard errors and regional fixed effects)

	Dependent variable:	
	Log Betweenness Centrality	
	Model during funding	Model after funding
	(1a)	(1b)
Time During BioRegio	-0.453^{***}	
	(0.060)	
Time After BioRegio		-0.172^{***}
		(0.057)
BioTech	-0.778^{***}	-0.997^{***}
	(0.077)	(0.082)
Interaction Term During BioRegio	-0.243^{*}	
	(0.128)	
Interaction Term After BioRegio		0.352^{***}
		(0.121)
Log Number of Patents	0.879^{***}	0.878^{***}
	(0.007)	(0.007)
East	0.630^{***}	0.629^{***}
	(0.042)	(0.042)
Avg Team Size	-0.232^{***}	-0.231^{***}
	(0.011)	(0.011)
Observations	28,304	28,304
R^2	0.382	0.382
Adjusted R^2	0.382	0.382
Residual Std. Error (df = 28274)	1.359	1.359
F Statistic (df = 29; 28274)	603.578^{***}	603.912^{***}

Note: *p<0.1; **p<0.05; ***p<0.01

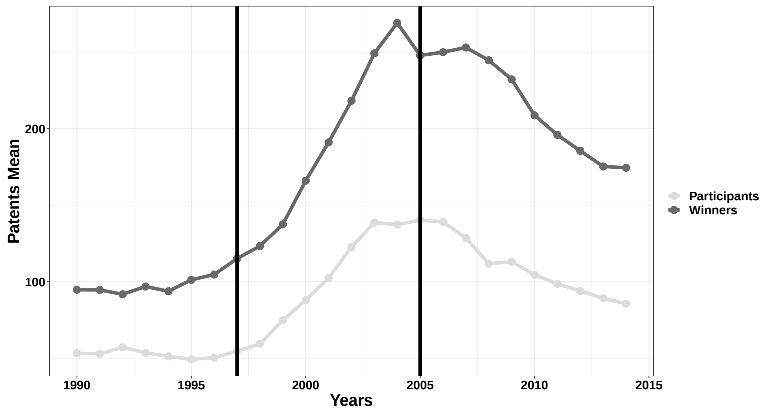


Figure 4.9: Number of patents over time (model 2 (table 4.7) treatment and control groups)

4.6.2 Biotechnology in winner and non-winner regions

Figure 4.9 shows the evolution of the average number of biotechnology patents in the treatment (winner regions) and control (non-winner regions) groups for model 2. Since in this case we use the same number of classes (only from biotechnology) among different knowledge spaces, it is possible to compare them by their averages. We observe that both curves have a similar development. Biotech classes both in winning and non-winning regions have a rather low average number of patents in the period before the funding, while in the period during funding, there is the peak for both groups and then finally a decrease in the period when funding ceased. This means that even if the curve for the winners is higher, there is no big difference in relative changes in patenting activity when comparing biotechnological classes in winning and non-winning regions. Nevertheless, as stated above, the number of patents it is not sufficient to assess if there was an increased interaction among the nodes in the knowledge space.

Table 4.6 shows the means of log betweenness, their differences and standard errors for control and treatment groups in model 2 for each year. The control group is mainly above the treatment group in terms of betweenness centrality. This situation changes only in the post-treatment period. In fact, here the gap is lower, and in some years, the treatment group is above the control group. This result gives already some insights on what to expect from the

DiD regressions. Moreover, the difference in means in the pre-funding period is never significant. So, the assumption of parallel trends, which is important for the DiD approach, cannot be rejected.

Table 4.6: Mean comparison of log betweenness centrality. Treatment and control groups as in model 2 (table 4.7)

Year	Participating Mean (Control group)	Winning Mean (Treatment group)	Difference	SE
		Pre-Treatment		
1990	5.755	5.341	-0.413	0.494
1991	5.789	5.253	-0.536	0.495
1992	6.082	5.252		0.444
1993	5.877	5.394	-0.483	0.467
1994	5.725	5.291	-0.434	0.481
1995	5.696	5.393	-0.303	0.477
1996	5.720	5.081	-0.639	0.515
		During-Treatment		
1997	5.822	5.330	-0.492	0.481
1998	5.561	5.453	-0.108	0.400
1999	5.664	5.406	-0.259	0.405
2000	5.702	5.528	-0.174	0.390
2001	5.752	5.447	-0.305	0.427
2002	5.806	5.378	-0.427	0.434
2003	5.694	5.383	-0.311	0.454
2004	5.606	5.531	-0.075	0.464
2005	5.636	5.412	-0.225	0.456
		Post-Treatment		
2006	5.686	5.718	0.032	0.441
2007	5.932	5.697	-0.235	0.475
2008	5.768	5.822	0.054	0.471
2009	6.035	5.988	-0.047	0.430
2010	6.139	5.931	-0.208	0.418
2011	6.142	5.991	-0.151	0.378
2012	6.073	5.871	-0.202	0.380
2013	6.130	6.174	0.044	0.398
2014	6.202	6.229	0.026	0.418

Figure 4.10 represents the DiD approach for model 2 using a base-line model without controls. Here, the result shown in table 4.6 become even clearer. Betweenness centrality increases steadily in both groups after the start of BioRegio. Before and during treatment, biotechnology in the control group (solid line) is structurally more embedded than in the treatment group.

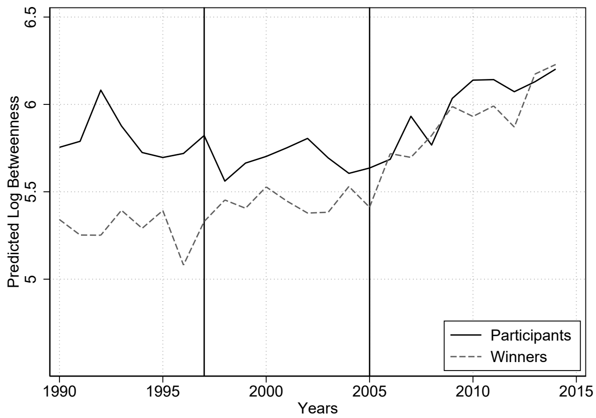


Figure 4.10: Fitted trends comparison for model 2

However, in the post-treatment period, biotechnology embeddedness in the two groups becomes more similar. The relatively lower embeddedness in the winning regions can be explained by their strength in several other fields so that initial embeddedness of biotech was lower despite absolute strength in terms of the number of patents. The sharper increase, in particular after funding, indicates long term changes in the knowledge space which might be induced by the policy.

To test this, in table 4.7, we present the results for models 2a and b. Model 2a evaluates if BioRegio had a significant impact on biotechnology embeddedness in the period when the policy was running, while model 2b evaluates the significance for the post-treatment period. For both models, it holds that winning regions show a significantly lower betweenness centrality than the control regions. With respect to period differences, the first model (2a) shows that betweenness centrality in the time during BioRegio is significantly lower than in the other periods. The second model (2b) delivers that for the time after BioRegio, there is no significant difference in betweenness centrality to the periods before. The interaction of time during BioRegio and winning region is positive but not significant. However, in the post-treatment period, the interaction term turns out positive and significant. This means that the biotech classes in the winning regions become more important than their corresponding classes in the non-winning regions. This result is quite important because it shows that when comparing biotech classes among regions (some affected by the policy and some not), the positive effect on betweenness is larger in the regions that won the contest. As such, winning regions have a knowledge space with better embedded biotechnological classes by the end of the considered period[5].

4.7 Conclusion

Innovation oriented cluster policies, such as the German BioRegio contest, have the potential to change the behavior of actors in terms of increased innovation activities and interaction (Engel et al., 2013; Graf and Broekel, 2020). Such effects, measured on the individual (firm) level, find substantial support in the literature (Nishimura and Okamuro, 2011; Mar and Massard, 2021). In that respect, they do not differ much from other types of innovation policies, such as general R&D subsidies. However, the ambition of cluster policies goes beyond increased innovation and interaction, and it also aims at more ample structural effects in terms of specific technologies pursued and links to other technologies intensified or newly created. For the purpose of evaluation of such policy targets, there is a need to identify respective policy impacts in a causal way. Since targeted structural effects might not show up in the short term, such evaluation studies need to focus, in particular, on long term effects. Complementing research on policy effects on the structure of actor networks (Graf and Broekel, 2020; N'Ghauran and Autant-Bernard, 2020), we investigated their impact on the regional knowledge space. As an interesting case, we took biotechnology and the BioRegio program in Germany. We studied changes in the embeddedness of biotechnology in regional knowledge spaces and how this was affected by BioRegio.

We argue that supported fields of activity, in our case biotechnology, should increase their visibility and importance within the knowledge space by either creating and/or intensifying links within the field itself (along existing trajectories) or by creating links with previously unrelated fields (cross-fertilization). Our descriptive analysis shows that in the four win-

[5] These results are robust to the selection of regions. We performed the same analyses with a more homogeneous subsample of regions. For each winning region, we manually select the most similar non-winning region in terms of the number of biotechnology patents during the pre-funding period and ran models 2a and b. Since the results do not change much (slightly higher model fit), we refrain from presenting them here. Tables are available upon request.

Table 4.7: Comparing structural embeddedness of biotech classes between winning and non-winning regions (DiD regression, robust standard errors and regional fixed effects)

	Dependent variable:	
	Log Betweenness Centrality	
	Model during funding	Model after funding
	(2a)	(2b)
Time During BioRegio	−0.496**	
	(0.245)	
Time After BioRegio		0.263
		(0.225)
Winning region	−0.820***	−0.899***
	(0.093)	(0.100)
Interaction Term During BioRegio	0.022	
	(0.152)	
Interaction Term After BioRegio		0.241*
		(0.144)
Log Number of Patents	0.727***	0.727***
	(0.020)	(0.020)
East	0.043	0.042
	(0.085)	(0.085)
Neighbour	−0.033	−0.033
	(0.083)	(0.083)
Avg Team Size	−0.252***	−0.249***
	(0.048)	(0.048)
Observations	2,872	2,872
R^2	0.278	0.279
Adjusted R^2	0.271	0.271
Residual Std. Error (df = 2841)	1.726	1.725
F Statistic (df = 30; 2841)	36.507***	36.623***

Note: *p<0.1; **p<0.05; ***p<0.01

ning regions, biotechnology was connected with many other fields in the knowledge space during funding. However, we also observed a decrease in those inter-technological linkages in the periods after the funding. In connecting biotechnology with other fields, all four winner regions showed distinct patterns of specialization. In Jena, for example, many links were established with medical technology, while in Rhineland, novel combinations with textiles and paper machines were developed. In general, many of the new combinations were with classes in the broader field of chemistry.

We complemented this dyad-based analysis with an econometric approach to assess the policy impact on the embeddedness of biotechnology within the knowledge space of supported regions. To measure embeddedness, we used betweenness centrality of IPC4 classes in the regional knowledge spaces and implemented it as the dependent variable in two sets of diff-in-diff estimations. In the first set, we compared biotech with non-biotech IPC4 classes in winning regions and find a positive effect of the policy on the embeddedness of the biotech classes only after the funding period. By focusing only on winning regions, this setting did not allow us to unambiguously identify policy effects, since increasing biotechnology embeddedness could also have been a result of a general technological trend. Therefore, in a second set of regressions, we compared biotechnology in winning and non-winning regions. Again, our results indicate a positive policy effect on the knowledge space integration of biotechnology only after the funding period. Given that patent applications increase substantially during the funding period but drop afterwards, this finding is somewhat startling. One reasonable interpretation would be that research during initial stages of BioRegio was concerned with incremental progress along the lines of existing research, while public funding via the BioRegio program allowed for research that was more risky and connected biotechnology with more distant technological fields. That type of research takes more time to develop, which might explain why such a transformative effect of the policy shows up only after the funding period.

Compared with other evaluations of the BioRegio program, our research implies that long term effects of cluster policies can be manifold. While neither Engel et al. (2013) nor Graf and Broekel (2020) find evidence for long term effects on innovation outputs or actor network structures, our findings show that the direction of the search process was shaped by the policy. We have to acknowledge, though, that our research approach did not allow for a comparison with other, simultaneous policy measures.

A generalization of our findings has limitations due to the nature of the analysis. First, like several other studies on the knowledge space, we rely on patents which limits our analyses to inventions that can be patented. As such, we miss many non-patentable inventions like advances in software and services. Second, our analysis relies on the patent classification system which implies that the patents classified within each class are assumed to be similar but substantially different from others. Since this classification is done by the patent offices for other reasons than this type of analysis, this might not hold true. Third, measuring treatment effects with moving windows is also subject to limitations. Immediate policy effects might be blurred since periods overlap. Fourth, since we do not control for other policies that support biotechnology, we cannot exclude that they had effects on the knowledge space as well. Generalizing the results to other cluster policies seems challenging, as each policy has its own objectives, characteristics and design features.

Future research should focus on the effects of these induced changes in the structure of the knowledge space on regional innovative and economic performance. This is fundamental, since the usage of performance indicators can really capture if a policy had an effect on the innovative activity of a region, whereas, the creation of new technological combinations cannot be directly translated to an increase in more and better innovations in the region.

4.8 Correlation Tables

Table 4.8: Correlation table for models 1a and b (table 4.5)

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
(1) Log Betweenness Centrality	-	-0.04***	0.02***	0.03***	0.59***	-0.07***	0.03***
(2) Time During BioRegio		-	-0.60***	0.00	0.02***	0.01***	0.02***
(3) Time After BioRegio			-	-0.01	0.05***	0.06***	-0.01***
(4) BioTech				-	0.20***	0.09***	0.11***
(5) Log Number of Patents					-	-0.16***	0.29***
(6) East						-	0.13***
(7) Avg Team Size							-

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

Table 4.9: Correlation table for models 2a and b (table 4.7)

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
(1) Log Betweenness Centrality	-	-0.06***	0.08***	-0.06***	0.47***	-0.09***	0.02	0.02
(2) Time During BioRegio		-	-0.59***	0.01	0.08***	0.02	-0.01	0.03
(3) Time After BioRegio			-	-0.01	0.08***	0.02	0.01	-0.08***
(4) Winning region				-	0.24***	-0.05***	-0.30***	0.23***
(5) Log Number of Patents					-	-0.15***	-0.04***	0.41***
(6) East						-	0.16***	0.19***
(7) Neighbour							-	0.07***
(8) Avg Team Size								-

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

Chapter 5

The influence of organizations on technological combinations: an application on German regions

5.1 Introduction

Inside a regional knowledge space (KS) (Kogler et al., 2013), technologies are considered important if they are able to connect several fields, thereby supporting technological development (Basilico and Graf, 2020). Authors can define these particular technologies in different ways based on their role in the technological space, famous definitions are: General Purpose Technologies (e.g. Bresnahan and Trajtenberg, 1995; Hall and Trajtenberg, 2004), Key Enabling Technologies (e.g. European Commission, 2009; Montresor and Quatraro, 2017) and Bridging Technologies (Basilico and Graf, 2020; Corradini and De Propris, 2017). However, the literature does not yet offer a perspective on which economic agents combine these technologies (Boschma, 2017). In this context, I am interested in the role of two distinct actor characteristics: i) the position of actors within the knowledge network in the respective region (Boschma, 2017) and ii) the particular role of public research in technological development (Graf and Menter, 2021; Graf and Henning, 2009).

Agents are considered important for knowledge development in the regional innovation network if they provide particularly important combinations of already existing technologies in the KS. These agents could drive regions to explore new technological trajectories through the introduction of novel technologies in the KS (Tanner, 2014; Gilbert and Campbell, 2015). The degree of novelty introduced in the KS is influenced by the nature of the organization (Miller et al., 2005) and its position in the RIN (Graf, 2017; Graf and Menter, 2021). On one hand the more the research orientation of a organization is towards basic research its attitude to combine "distant" knowledge increases. On the other hand the more the organization is central in the network the more has access to diverse knowledge from different sources. These two forces are complementary and they influence the propensity of the organization towards knowledge recombination processes. The aim of this paper is to assess under which circumstances organizations with specific characteristics combine knowledge differently from others.

To understand how organizations combine knowledge I constructed two different networks for each Labour Market Region (LMR) in Germany using patents as main data source. The first network is a Knowledge Space (KS) (e.g. Quatraro, 2010; Kogler et al., 2013) and the second one is a "innovator network" (e.g. Graf, 2017). The simultaneous construction of the two networks is important since on one side from the KS information about how different organizations combine knowledge is collected and on the other side information on how central a single organization is inside the Regional Innovation Network (RIN) is also collected. In both cases measures taken from Social Network Analysis (SNA) are performed to retrieve the relevant information.

In the case of KS I decided (after analysing the different characteristics of the widely used indicators in Social Network Analysis) to use the so-called Redundancy Coefficient (RC) Latapy et al. (2008). This indicator is used to assess if organizations are combining knowledge important for the KS itself. In other words, this measure permits to identify organizations that combine technologies that no one else combines in the KS. These important organizations, when removed, should affect the cohesiveness of the KS to a higher degree than others. In the case of the "innovator network" I measured degree centrality for each applicant to assess how central it is in the RIN. To characterize these organizations, I run a series of regressions with the RC for each applicant as the dependent variable and the rank degree centrality as independent variable. Moreover, I have included a series of dummy variables able to identify the different typology of the organizations. The results show that public research institutes involved in the production of basic research activities combine knowledge that it is not important for the cohesiveness of the KS. Therefore, they introduce to a lower degree different combinations in the KS. Private research institutes are more important for the cohesiveness of the KS. Thus, they introduce more different combinations than others.

However, when the variables for the identification of the research orientation of organizations are interacted with the degree centrality on the "innovator network", the results are different. With an increase in centrality of basic (public) research institutes in the RIN there is an increase in importance for the technological structure of the region, enabling the possibility of introducing unique combinations in the KS. Therefore, in the case of public research institutes, both the orientation of the considered organization and the embeddedness in the RIN matter for the cohesiveness of the KS. These findings are also relevant for policymakers. Policy makers should stimulate public research institutes by promoting collaboration with private institutes so that they hold central positions in the RIN. Only when public research institutes are central in the RIN can combine technologies important for the KS and, possibly, introduce highly impactful technological innovations (Graf and Menter, 2021).

The remainder of the paper is organized as follows. Section 5.2 provides an extensive literature review on knowledge production, innovation, technologies and the role of agents in the technological recombination processes. I introduce the different typologies of considered applicants in Section 5.3 along with a presentation of the database. Section 5.5 presents the main dependent variable, namely the *Redundancy Coefficient* along with a descriptive analysis of its features on a selected number of regions. Section 5.6 presents the econometric approach, a description of the utilized variables and some descriptive statistics. Section 5.7 presents the main results of the

Tobit regressions. Finally, Section 5.8 concludes and discusses the main implications of the paper.

5.2 Literature Review

5.2.1 Technological Combinations and the Knowledge Space

The origin of a technological innovation stems from the recombination of already existing knowledge and technology to reach a specific purpose (Nelson and Winter, 1982; Weitzman, 1998; Sorenson and Fleming, 2004). This combination process is characterized by the degree of two different dimensions: the relatedness between the components and the uniqueness of their combination (Arts and Veugelers, 2015).

The concept of relatedness has been used to measure the importance of knowledge spillovers (Rosenberg and Frischtak, 1983; Pavitt, 1984; Jaffe, 1989). Moreover, it has been adopted widely to measure the complexity and the production of knowledge in time and space (Boschma et al., 2013; Boschma, 2017). In its general formulation, the closer a technology is with another one, the more they are related. When two non-related technologies are combined, the possibility to develop exceptional innovations increases (Ahuja and Lampert, 2001).

The set of technologies embedded in a nation or region (and therefore their "distances") is usually represented in a network form, and this can take the name of Knowledge Space or Technological Space (Quatraro, 2010; Kogler et al., 2013). In the KS nodes are the technological components and the links their relations. Here, different types of connections are present in which some components are directly linked, and yet others are connected only through indirect links. As Broekel (2019) shows, for example: "in regard to airplane technology, the components' wing design and aluminium processing are directly linked, while electronic navigation is only indirectly related since other components (e.g., electronic control systems, mechatronic interfaces) act as bridges". In this case, everything that is related to the electronic navigation of an airplane has a bridging function acting as indirect links between electronic and aircraft technologies. Therefore, these bridges are connecting many other components, establishing indirect links among them being important for the cohesiveness of the network (Basilico and Graf, 2020).

The ability to be an indirect connector of many other technologies is called *pervasiveness*. Through the indirect connection of many components, these technologies could drive the economic development of a region or initiate a new technological paradigm (Bresnahan and Trajtenberg, 1995). These technologies are usually identified as General Purpose Technologies (GPTs) or with their subgroup Key Enabling Technologies (KETs) (e.g. Hall and Trajtenberg, 2004; Montresor and Quatraro, 2017). These technologies (GPTs, KETs and Bridging Technologies) and their combinations can be mapped inside a KS. Through the usage of measures from Social Network Analysis (SNA) their relations and their importance for the cohesiveness of the KS has been already demonstrated in the literature (Basilico and Graf, 2020).

Other prominent studies show how already existing technologies can be combined in new ways to introduce innovative activities (Arts and Veugelers, 2015). Arthur (2009) refers to this process as *combinatorial evolution*. Novel technologies arise when old components that were never combined before are integrated. In this sense, the newly created technology grows in complexity over time because in every new step in the technological evolution, something more technically complex is obtained. The inventions that result from this recombination process can, eventually, embed high novelty that leads to important new discoveries (Weitzman, 1998). However, not only do unique combinations exist, combinations also occur along well-defined paths. The combination of already existing technologies in unique ways requires exploration, whereas the combination of technologies along already defined paths requires exploitation. The former leads to technological breakthroughs, while the latter leads to incremental technological improvements (Fleming and Sorenson, 2001; Arts and Veugelers, 2015).

This recombination approach is important also for the aforementioned relatedness. When two previously unrelated technologies are continuously combined, their relatedness increases (Castaldi, Frenken, and Los, 2015).

Therefore, relatedness can be regarded not as a static but as a dynamic force (Boschma, 2017). However, the potential for developing breakthrough technologies resides in the combination of previously unrelated pieces of knowledge, even if the probability of failing in this case is higher (Saviotti and Frenken, 2008). In this sense, the younger is the technology that resulted from the recombination process, the higher is the potential to develop breakthrough innovations. Whereas after the same components have been combined in a certain way many times only incremental innovations would appear. However, the probability that novelty emerges directly only from new combinations or exclusively from old ones it is quite rare, and in reality it is a mix of both processes (Boschma, 2017).

In literature studies focus on the relatedness and its effects on diversification on the regional or national level. For example, Frenken, Van Oort, and Verburg (2007) find that when regions embed related activities, it is easier for them to successfully recombine technologies. However, the combination between unrelated technologies could also occur in regions. Castaldi et al. (2015) shows how regions with higher unrelated variety possess a higher potential to develop breakthrough innovations. Nonetheless, they show that regions with higher related variety are the ones that combine technologies but with a lower potential for radical inventions.

5.2.2 Cognitive and Geographical Spillovers

Knowledge used to produce exceptional technological innovations and thereby introduce new paradigms has specific characteristics. Dosi (1988) identifies as an important asset for technological improvement the exploitation of both private (tacit and protected knowledge) and public knowledge (knowledge available to all economic actors embedded in a region or a country). The latter has the ability to diffuse among industries and economic actors through spillovers, whereas the former is transmitted with more difficulty. Spillovers can be classified in geographical, cognitive, organizational, social or institutional (Boschma, 2005). Despite differences in definitions, these different forms of spillovers are all able to reduce uncertainty and increase coordination among the actors involved (Breschi and Lissoni, 2009). Therefore, they facilitate knowledge transfer and the subsequent undertaking of innovation activities (Boschma, 2005).

In this paper I am mostly interested in the characteristics and effects of cognitive and geographical spillovers. Cognitive spillovers is intended as the process of knowledge sharing between actors having similar capabilities (Nooteboom, 2000). However, if the two actors involved in knowledge sharing are cognitively too similar, this could sabotage the learning process. This deficiency is caused by the necessity of both dissimilar and complementary knowledge in producing the most benefits from spillover effects. Different and novel knowledge enhances creativity (Cohendet and Llerena, 1997). However, if the two actors are cognitively too distant, their absorptive capacities are limited (Boschma, 2005). If the cognitive distance is too low, there is a lack of novelty whereas if the cognitive distance is too high, communication problems could arise. Therefore, an optimal cognitive distance, one which is neither too large nor too small, is necessary for stimulating interactive learning (Nooteboom, 2000). This problem can be solved through geographical spillovers. The presence of a common knowledge base coming from different sources inside a geographical cluster can trigger cognitive spillovers (Maskell, 2001; Boschma, 2005). Moreover, spillovers are usually identified as geographically concentrated, making it difficult to disseminate knowledge over long distances (Fritsch and Franke, 2004; Acs, Anselin, and Varga, 2002).

Proximity facilitates the passage of knowledge among different entities through spillover activities (Boschma, 2005). The higher spillover activities are in a specific location the more knowledge is accumulated, increasing the complexity embedded in the area. Knowledge complexity is defined as the ability to combine multiple and diverse skills (Zander and Kogut, 1995). The production of complex knowledge is not a simple task, and it requires huge economic efforts. As a result, complex knowledge is an exclusive asset not publicly available to all economic actors (Rivkin, 2000). The production of complex knowledge requires continuous feedback, in this sense strong ties between actors are necessary (Boschma, 2005). The higher is the complexity of knowledge, the stronger the collaboration ties among the actors must be to achieve a fruitful transfer (Hansen, 1999). Moreover, the presence of complex knowledge embedded in a specific location is a determinant factor for its economic success and to achieve a competitive advantage (Fagerberg, Verspagen, and Caniels, 1997; Glaeser, Kallal, Scheinkman, and Shleifer, 1992; Jaffe, Trajtenberg, and Henderson, 1993; Kogler et al., 2013; Hidalgo and Hausmann, 2009; Boschma, 2005).

5.2.3 The role of agents in the Technological Recombination Process

The agents (organizations and firms) present locally are the micro-units where knowledge and technological elements are combined in the pursuit of innovative activities. As denoted by Boschma (2017), a micro-perspective on which are the agents responsible for combining technologies important for the structural composition of the KS and therefore spur innovation in the region is missing. Inside the KS, there are two forces influencing the propensity of agents to combine technologies differently than others: the first is the position they occupy within the Regional Innovation Network, and the second is their orientation towards basic or applied research (Graf and Menter, 2021). These forces are not completely separate but affect each other, as will be explored in the following.

Firstly, it is important to understand how knowledge can be combined differently when the interested agent resides in the center of the innovation network or in the periphery. To analyze this, the theory of knowledge spillovers could help. Spillovers, as already explained in subsection 5.2.2, are an important factor for growth through knowledge flows, and subsequently they influence the production of innovative activities (Griliches, 1992). Acs, Braunerhjelm, Audretsch, and Carlsson (2009) identifies spillovers as an important source for identification and exploitation of entrepreneurial opportunities. Therefore, if an agent is embedded in a region where many innovative activities are produced, its chances of having higher than average innovative and economic performance are higher (Powell, Koput, and Smith-Doerr, 1996). Knowledge usually flows not only between two actors but also through many components in the network, therefore being positioned in the center gives greater opportunities for knowledge recombination (Graf, 2017; Graf and Menter, 2021).

Many studies considered the concept of centrality as the main measure to assess the embeddedness of entities in a regional network (Freeman, 1978). The higher is the centrality of the considered entity, the more it influences the knowledge flows, thereby affecting the frequency of combinations inside the network. As denoted by Rowley, Behrens, and Krackhardt (2000), an entity that is positioned inside a dense network has higher possibilities for exploitation, whereas agents embedded in a sparse network are explorers. As already pointed out in subsection 5.2.1, exploitation can eventually lead to incremental innovations, whereas exploration is conducive to radical innovations. This is confirmed by Hervas-Oliver, Lleo, and Cervello (2017) where they argue that actors in the center of the network hesitate to develop radical innovations because these are risky activities and could lead to the loss of their previously achieved status. However, these studies focus only on firms and do not consider the fact that a region is composed by different typologies of actors. Usually universities and public organizations occupy a central position in the regional innovation network because of their knowledge transfer activities, therefore they should be considered separately (Graf and Krüger, 2011). In this sense, Graf and Menter (2021) find that the centrality of organizations increases the possibility to develop radical innovations.

Not only the embeddedness of actors inside the regional innovation network influences the propensity to combine knowledge in a different way, but also the scientific orientation (basic vs applied) plays a role. Basic research, in the classic view, is focused on introducing new revolutionary technological combinations without a clear application. Whereas applied research is usually redefining knowledge that is already existing to produce and commercialize products and services (Miller et al., 2005; Graf and Menter, 2021). Moreover, the role of public research changed over time, departing from this classical dichotomy. Basic research organizations have been allowed to directly translate new findings into intellectual property rights with the appropriation of the outcomes (Etzkowitz, 2004). This shift pushed universities and research organizations to assume a more entrepreneurial orientation. They started to undertake new activities ranging from patents applications to consultancy, making the boundaries between applied and basic research blurry (Leyden and Menter, 2018). Therefore, the assumption that basic research is only focused on combining different knowledge to initiate new technological waves does not, necessarily, hold true anymore. It is important to understand how the access to a variety of knowledge sources, given by the fact that basic research organizations usually occupy a central position in the collaboration network, is mitigated by the shift to a more applied research orientation.

Summing up, centrality surely matters for the quality of inventions, but it depends also on the typology of the considered organization. However, a perspective on how the mitigation effect carried out by centrality matters on the typology of technological combinations is missing in the literature. This point of view would allow us to better ascertain if central actors in the regional innovation network are also combining important knowledge present locally, enabling opportunities for innovative activities and ultimately permitting regional economic growth.

5.3 The German research infrastructure

The research infrastructure is the set of private and public organizations present in the country dedicated to research purposes. The main aim of the paper is to assess how different types of organizations are combining knowledge inside the KS. As a practical application, I consider the German research infrastructure, where heterogeneous organizations in terms of funding sources are present. Germany is composed both by private and public entities that do research in different fields of studies. Germany has around one thousand research organizations that are publicly funded (BMBF, 2017). There are around 340 universities (120 *Universities* and 220 *Polytechnics*). Graf and Menter (2021), based on BMBF (2012, 2014, 2020) ordered public institutes based on two factors: the degree of funds received from public sources and the type of research output (patents over publications). The first factor implies that the organization that receives the highest share of funds from public sources is regarded as the most basic research organization. The second factor implies that the organization that has a lower ratio between patents and publications is regarded as the most basic one. Then these two rankings are aggregated and, the final order of the organizations (from basic to applied research) is the following:

- The *Max Planck Society* consists of 86 institutes with more than 23000 employees. The focus of their research activity is on natural sciences, life sciences, humanities and social sciences.
- The *Leibniz Association* consists of more than 90 research institutes with around 20000 employees. The focus of their research is broad, covering various subjects from natural to social sciences.
- The *Helmholtz Association* is the biggest German scientific association. It consists of 19 research centers with around 40000 employees. The main focus of their research is on these areas: (1) energy; (2) earth and environment; (3) health; (4) aeronautics, space, and transport; (5) matter and (6) key technologies.
- *Fraunhofer* is a leading organization in Europe which is mostly focused on applied research, It includes 72 institutes with more than 26000 employees. The institutes are focused on the following research areas: (1) health, (2) security, (3) communication, (4) mobility, (5) energy and (6) environment.

Therefore, the scientific orientation of these organizations is affected by the different degree of private funding they receive. The more the institute receive funding from public sources, the more its focus is on basic research (Graf and Menter, 2021).

5.4 Data

The OECD, REGPAT database, January 2020 is used to select patent applications filed between 2010 and 2015 that have at least one inventor located in Germany. While patent data have been used in many empirical applications, their availability and the amount of information that they provide increased their popularity. However, patents do not capture all the knowledge produced in an economy, and firms can also protect their knowledge in other ways (Kogler et al., 2013; Griliches, 1990).

The Labour Market Region (LMR) is used to identify the regional areas in the German KS. LMRs are larger than the standard NUTS3 regions (smaller units which separate two different regions, the city and the surroundings) because they account also for commuters that are traveling each day to reach the workplace. For my purposes, it suffices to capture technological combinations on a wider perspective than NUTS3 regions, allowing for a higher number of observations. To permit the participation of an adequate number of applicants for each geographical entity, only regions with at least 147 patents (corresponding to the 15% quantile of the distribution) in the period are included. All the patents filed in a specific region from 2010 to 2015 (snapshot) are used to reconstruct the KS.

In a similar fashion as Graf (2017), a patent is assigned to a LMR if at least one inventor is located there. This is particularly important since applicants tend to register their patents only in their headquarters. Therefore, with this procedure, a high concentration of patents in few regions of Germany is avoided. Following Graf and Menter (2021) using the Regpat HAN database, patents are associated using an algorithm to the organizations that filed them. The included organizations are the ones already described in subsection 5.3 with firms as an additional category.

Firstly, to construct the knowledge spaces of each LMR, information of the IPC classes listed in each patent has been used. The node of the network is a single IPC 4 digits class and the edges are patents that co-classify two or more of these classes. The applicants that do not create any combination are removed from the sample. Secondly, to construct the "innovator networks" information about applicants and inventors is collected. In this case the node of the network is an applicant present in the region and the edges are inventors listed by two or more applicants in different patents.

Table 5.1 shows the number of patents belonging to each group of applicants. As expected, private institutes are the group with the highest number of patents. This is because the number of private institutes applying for a patent in the period from 2010 to 2015 is much higher than other groups. However, the number of patents on average for each private institute is lower than for other groups. This means that many small private institutes are included. The category "others" represents the applicants not identified in any other category. These are individual inventors or registered associations which are not identified as private companies or a specific organization among

Table 5.1: Number of patents for each category of applicant

Category	Nr. Applicants	Nr. Patents	Average Patents
Max Plack Institute	51	677	13.27
Leibniz Institute	48	172	3.58
Helmholtz Institute	20	115	5.75
University	362	2492	6.88
Technical University	148	1017	6.87
University of Applied Sciences	73	142	1.95
Fraunhofer Institute	133	3438	25.85
Private Institutes	12537	134602	10.74
Other	1408	7041	5.00
Total	14780	149696	10.13

the ones described in section 5.3. This category of applicants is excluded from the analysis because it is difficult to assign their attitude towards applied or basic research since it is composed by a set of non-homogeneous individuals and single research institutes (not affiliated to *Max Planck Society*, *Leibniz Association*, *Helmholtz Association* or *Fraunhofer*).

For clarification purposes it is important to specify that the “Nr. Applicants” column counts multiple times the same applicant for each category. This happens because each patent is assigned to a region based on the inventor location, therefore the same applicant can be matched with many regions. This is the unique reason why the numbers do match up with what has been specified in section 5.3.

5.5 The Redundancy Coefficient

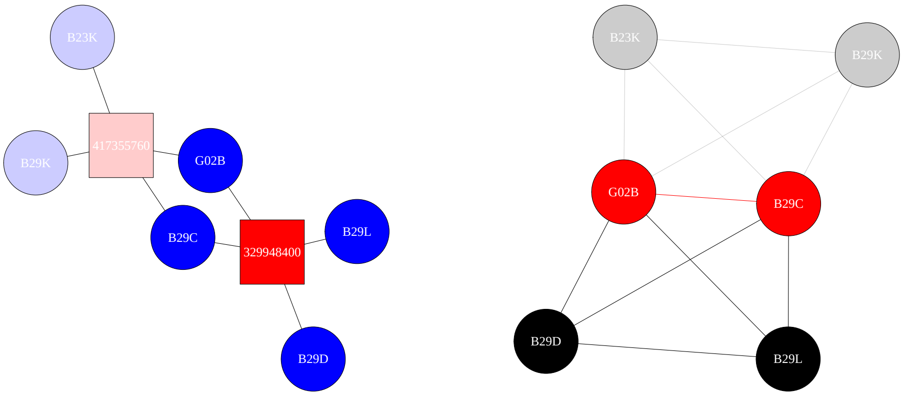
5.5.1 The conceptualization of the Redundancy Coefficient

The main intent of this paper is to measure how different organizations combine components in a different way with respect to others. In the subsequent paragraphs I analyse the characteristics of some measures used in Social Network Analysis to find the right indicator for my analysis.

Density is the number of existing ties divided by the number of potential ties. One possible application would measure network *density* before and after the removal of a single applicant. However, *density* is not informative when comparing networks (regions) of different sizes (Graf, 2017). Since my setting is composed by regions with different dimensions, this measure is not suitable. A possible alternative would be to measure the *mean degree* in both situations. This measure shows the average number of connections, and it is well suited to compare networks with different sizes. However, the value expressed by the *mean degree* could be high because one node has many connections with others, pushing the mean to a higher level (Graf, 2017). Therefore, the removal of this single node causes a substantial drop of the cohesiveness. This, in theory, could be good for my setting since I want to capture the relation between applicants and important technologies. However, organizations combine knowledge in a unique way (different from others) to pursue innovation, so this effect would not be captured using only *degree centrality*. Other cohesiveness measures like *connectedness*, *fragmentation*, *average distance* and *clustering coefficient* are focused on the distribution of the links in the network, but they do not tell anything about the importance of the combinations. Therefore, to correctly address how important are single combinations for the cohesiveness of the network, I decide to present another (new) indicator.

The cohesiveness of the KS should be affected differently depending on how applicants combine technologies. Applicants combining technologies that no one else is matching in the KS should affect the general cohesion of the KS at a higher rate. To detect this phenomenon, I introduce the Redundancy Coefficient (RC). This indicator is first theorized by Latapy et al. (2008) for a variety of large two-mode networks. In the following paragraphs, I explain how the RC works on a real-world example from the database.

For example, I have chosen two patents from the KS of Jena. These patents have two different application IDs ("417355760" and "329948400"), and they belong to two different organizations (Fraunhofer Institute and Jenoptik AG). Figure 5.1a shows a two-mode network in this situation. The red nodes (squares) are the patents, whereas the blue nodes (circles) are the technologies. The 4-digit CPC classes "G02B" and "B29C" co-occur in both patents, while the other classes are present only in one of the two. Figure 5.1b represents the one-mode projection of the same graph and helps with the comprehension on how the RC works. If the patent "417355760" is removed from this network, then among the combinations made by this patent, only



(a) Two-Mode Network **(b)** One-Mode projection

Figure 5.1: Two-Mode network and its One-Mode projection: an example

the red edge between "G02B" and "B29C" survives. To understand the setting even better, the shaded nodes and links in figure 5.1 are the ones that would disappear if "417355760" is removed.

In the example illustrated in Figure 5.1, the RC for patent "417355760" would be:

$$rc(p) = \frac{|\{\{u, w\} \subseteq N(p), \exists p' \neq p, (p', u) \in E \text{ and } (p', w) \in E\}|}{(|N(p)|(|N(p)| - 1))/2} = \frac{1}{5} = 0.2 \tag{5.1}$$

Formally, assuming that p is a secondary node in the two-mode network (a patent in Figure 5.1a), $rc(p)$ is the fraction of edges of a generic node p linked to another node than p. In the one-mode projection, these edges would survive even without p (Latapy et al., 2008). With $rc(p) = 1$ the one-mode projection would not change after the removal of p, whereas if $rc(p) = 0$ none of the neighbors (N) would be linked together in the projection. However, this indicator would account only for redundancies on a single patent. Since the focus of this paper is on the applicants and their role in combining technologies in the KS an evolution of the aforementioned RC must be calculated.

Let's assume that a hypothetical network exists and that it is composed of only the patents from two applicants called Fraunhofer Institute and Jenoptik AG. Jenoptik with its patents creates 29 technological combinations, and when all the patents from this applicant are removed, only 7 combinations will survive.

In this case, the redundancy coefficient on the level of an applicant a would be:

$$rc(a) = \frac{n_s}{n_a} = \frac{7}{29} = 0.241 \tag{5.2}$$

Where $rc(a)$ is the number of edges that would survive (n_s) to the removal of all patents of a divided by the total number of edges (n_a) created by the patents of a. When $rc(a) = 1$, the one-mode projection remains the same without all the patents belonging to a. However, when $rc(a) = 0$, all the neighbors of all the patents belonging to a are disconnected. This measure is able to show how the applicant is redundant in combining technologies in the KS. Therefore, this coefficient actually shows how different applicants combine knowledge inside the KS and which are the most unique ones. I expect that the cohesiveness of the network drops when the least redundant applicants are removed because these combine knowledge not available to others in the KS. Merely the patents with only one applicant listed are removed from the KS to calculate the Redundancy Coefficient.

5.5.2 The Redundancy Coefficient applied on selected regions

To show the properties of the $rc(a)$ indicator and how the cohesiveness of the KSs are influenced by the removal of applicants with different redundancy degrees, an example on the regions Berlin, Düsseldorf, Munich and Stuttgart is performed. These four regions have a similar applicant structure, and they are among the most important German KSs (as showed in table 5.2).

Following Toth et al. (2022), for each region, patents are sequentially removed starting from the most redundant applicant to the least. At each stage, the *mean degree* is calculated to evaluate how the network is reacting and is

Table 5.2: Number of applicants in selected regions

Type	Region			
	Düsseldorf	Munich	Stuttgart	Berlin
Max Planck Society	1	1	1	2
Leibniz Association	0	0	0	2
Helmholtz Association	0	0	0	6
Universities	8	15	13	10
Technical Universities	10	8	4	8
University of Applied Sciences	6	3	1	10
Fraunhofer Institutes	3	2	1	3
Private Institutes	392	425	415	376
Other	56	62	41	86
Total	**476**	**516**	**476**	**503**

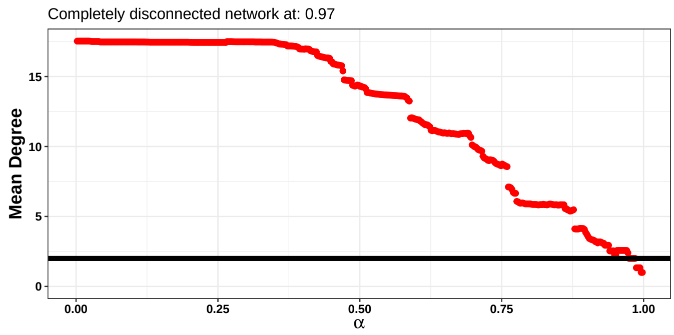
eventually becoming more disconnected. As previously explained, the *mean degree* is not suitable when the aim is to assess how applicants combine technologies, but it can give a good indication of how the cohesiveness of the network is reacting to the removal of some of its components (Molloy and Reed, 1995).

The mean degree is calculated as follows (Wassermann and Faust, 1994):

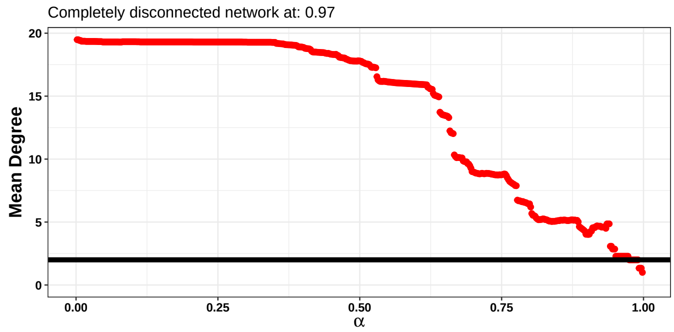
$$\bar{d} = \frac{\sum_{i=1}^{n} d_i}{n} \tag{5.3}$$

d_i is the degree of a single node and n is the number of nodes of the network. When the mean degree reaches the critical value of 2, it means that the network is completely disconnected. In the literature, this threshold is identified as the Molloy-Reed criterion, the point after which the network is fragmented in too many components (Molloy and Reed, 1995). The technological base of the regional KS would be completely dissolved (Toth et al., 2022).

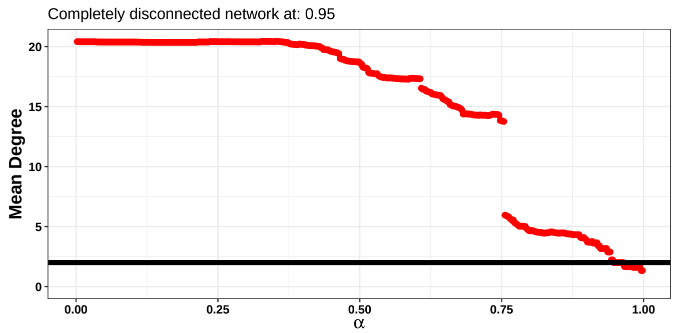
Figure 5.2 shows the results for the aforementioned procedure. On the abscissa is represented the mean degree calculated every time an applicant from the region is removed, on the ordinate is represented the parameter α that goes from 0 to 1. When α is 0 means that no patents from any applicant has been removed from the KS, when α is equal to 1 means that all applicants with their patents have been removed from the KS. All four networks become completely disconnected when around 95% of applicants are removed. When the first 50% of applicants are removed (the ones that combine at a higher rate knowledge already combined by others), the *mean degree* of the four KSs does not fall by much. However, when the least redundant applicants are removed, the mean degree drops dramatically. This finding confirms that the least redundant applicants have a bigger impact on the cohesiveness of the KS. Moreover, some substantial drops in the mean degree for all four KSs show that there are applicants creating many connections. These applicants have the highest number of patents in the region (big firms with many applications). Therefore, they are contributing to create a high number of connections in the region, once they are removed they are responsible of a huge drop in the mean degree. For example, the big drop in mean degree in Stuttgart from 13.76 to 5.95 is due to the presence of a big company *Robert Bosch GMBH* that alone is detaining 2299 patents and creates 1986 edges in the regional knowledge space. For this reason, in the econometric analysis that will follow the number of patents that each applicant has will be used as a control variable.



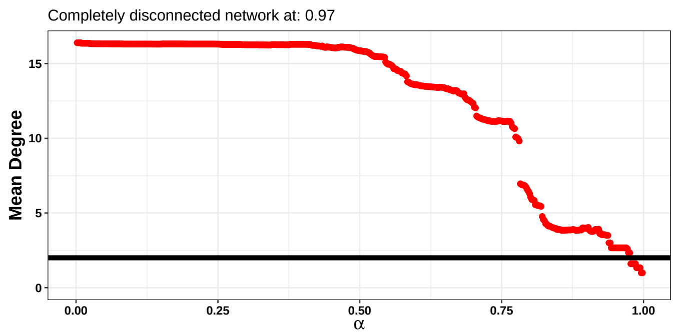
(a) Düsseldorf



(b) Munich



(c) Stuttgart



(d) Berlin

Figure 5.2: Sequential removal of applicants and mean degree calculation on selected regions

5.6 Econometric Approach

In this section I show the econometric approach that I used to understand how different typology of organizations combine knowledge. In particular, I am interested not only generally on their cross-fertilization abilities but also, and more importantly, if there is a mitigation effect due to their position in the Regional Innovation Network.

5.6.1 Dependent, Independent and Control Variables

Table 5.3 shows the variables used for the series of regressions. The impact of the combinations created by the applicants on the KS is assessed through the *Redundancy Coefficient* (already presented in section 5.5) that acts as dependent variable.

The first set of independent variables (*Type Max Planck*, *Type Leibniz*, *Type Helmholtz*, *Type University*, *Type Technical University*, *Type University of Applied Sciences*,*Type Fraunhofer*, *Type Private Institutes*) is represented by dummies to indicate the type of applicant. These dummy variables take value one if the name of the applicant inside the HAN database matches a specific applicant category. For the variable *Rank Degree Centrality*, regional "innovator networks" (applicants are nodes and common inventors are edges) have been constructed for each considered LMR. The degree centrality for each applicant is measured in each network and then ranked from the highest to the lowest result. In the literature, the "innovator network" is used to assess the potentials for knowledge spillovers among innovative actors inside a region (Graf, 2017). It follows that with this variable, the actual importance of the applicant for knowledge diffusion inside the regional innovation network is also assessed. The rank afterwards is reversed to aid interpretation of the results (high values in the reversed measure mean low ranks). The reversed rank degree centrality take values between 0 and 1, inclusive. A value of 1 indicates that an applicant is first in terms of degree centrality in the region, and a value of 0 means that the applicant is last in terms of centrality in the region.

The *Rank Degree Centrality* is then interacted with the typology of the applicant to assess whether when a specific typology of applicant is central has also an effect on its redundancy coefficient. This is particularly important for public organizations, since they usually occupy a central position and act as moderators and distributors of knowledge inside the regional innovation network. If the degree centrality of the applicant indeed decreases with its redundancy, then these agents could enable radical innovations as they combine knowledge in a unique way.

Finally, the *Number of Patents* is employed as the main control variable. This variable counts the number of patent filings of each applicant in each KS. The inclusion of this variable is necessary since the *Redundancy Coefficient* is affected by the number of patents. As already explained in the description of figure 5.2, the removal of applicants with many patents would affect the cohesiveness of the network to a higher extent. Furthermore, there are many applicants with only few patents in the dataset. To account for this, I use the logarithmic form to get to a normal distribution.

Table 5.3: Variables used in the regression

Variable Name	Description
	Dependent Variable
Redundancy Coefficient	Redundancy Coefficient calculated on each applicant present in the sample
	Independent Variables
Type Max Planck	Dummy variable that takes value one when the applicant is identified as Max Plack Society
Type Leibinz	Dummy variable that takes value one when the applicant is identified as Leibniz Association
Type Helmholtz	Dummy variable that takes value one when the applicant is identified as Helmholtz Association
Type University	Dummy variable that takes value one when the applicant is identified as University
Type Technical University	Dummy variable that takes value one when the applicant is identified as a Technical University
Type University of Applied Sciences	Dummy variable that takes value one when the applicant is identified as a University of Applied Sciences
Type Fraunhofer	Dummy variable that takes value one when the applicant is identified as Fraunhofer Institute
Type Firms	Dummy variable that takes value one when the applicant is identified as Firm
Rank Degree Centrality	Rank degree centrality of the applicant in the applicant-inventor network (reversed)
Interaction Terms Degree Rank vs Type Dummies	Groups of interaction terms between the type of the considered applicant and the rank degree centrality
	Control Variable
log(Number of Patents)	Number of patents for each applicant in logarithmic form

Table 5.4: Descriptive statistics

Variable Name	N	Mean	SD	Min	Max
	Dependent Variable				
Redundancy Coefficient	14780	0.534	0.362	0.000	1.000
	Independent and Control Variables				
Type Max Planck	14780	0.003	0.059	0.000	1.000
Type Leibniz	14780	0.003	0.057	0.000	1.000
Type Helmholtz	14780	0.001	0.037	0.000	1.000
Type University	14780	0.024	0.155	0.000	1.000
Type Technical University	14780	0.010	0.100	0.000	1.000
Type University of Applied Sciences	14780	0.005	0.070	0.000	1.000
Type Fraunhofer	14780	0.009	0.094	0.000	1.000
Type Private Institutes	14780	0.848	0.359	0.000	1.000
log(Number of Patents)	14780	1.174	1.190	0.000	8.276
Rank Degree Centrality	14780	0.149	0.125	0.050	1.000

Table 5.5: Average Rank Degree Centrality in regional innovator networks by group of actors

Type	Average Rank Degree
Max Planck	0.19
Leibniz	0.18
Helmholtz	0.17
University	0.20
Technical University	0.19
University of Applied Sciences	0.14
Fraunhofer	0.34
Private Institutes	0.15

5.6.2 Descriptive Statistics

Table 5.4 shows the descriptive statistics for the variables used in the regressions. The dummy variables show that almost 85% of the sample is composed by private entities, while the other public entities add up to around 5% of the sample. The total does not sum up to 100% because there 10% is identified as "others". As previously explained, this group has been excluded from the main empirical analysis. The table 5.7 in the appendix 5.9 shows the correlations among the variables.

Table 5.5 shows the average rank degree centrality in the regional "innovator networks" for each considered group of applicants. This confirms the assumption that public entities are on average more central than private organizations. In fact, *Private Institutes* have one of the lowest average degree centrality (together with *University of Applied Sciences*) when compared to the other groups.

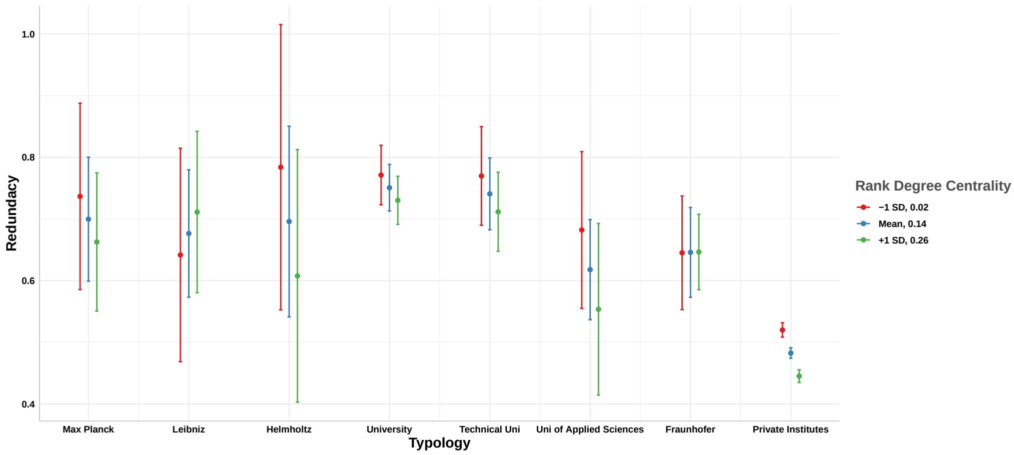


Figure 5.3: Predicted effects with different levels of Rank Degree

Figure 5.3 shows the redundancy coefficients at different levels of rank degree centrality for each group of applicants. In general, in all groups apart from the *Leibniz Institutes* and *Fraunhofer Institutes*, redundancy drops when the rank degree centrality increases. This means that when the applicant interacts more with others, it has access to more knowledge sources and combines technologies differently than others. The confidence intervals displayed in the figure have different lengths because of the number of participants identified in each group. The precision of the coefficient is higher when the number of applicants identified in one group is higher. *Private Institutes* have a higher precision because they are more numerous. In order to assess the least redundant applicants and the ones that have the highest impact on the cohesiveness of the KS, it is necessary to consider implementing an econometric approach.

5.7 Results

Table 5.6 shows the results for the econometric approach. Models 1 and 2 are OLS standard regressions, whereas models 3 to 5 include regional fixed effects. Model 1 shows the results which include only the dummy variables that distinguish the typology of applicant. Model 2 additionally controls for the *Number of Patents*. Model 3 introduces regional fixed effects. Model 4 additionally includes the *Rank Degree Centrality* as an independent variable. Finally, model 5 uses all variables with the addition of the interaction terms.

Starting from the first eight dummy variables (*Type Max Planck*, *Type Leibniz*, *Type Helmholtz*, *Type University*, *Type Technical University*, *Type University of Applied Sciences*, *Type Fraunhofer* and *Type Private Institutes*), the public organizations that are more redundant are: *Max Planck*, *Fraunhofer*, *Universities* and *Technical Universities*. These have a positive coefficient, meaning that, to a higher extent, they combine knowledge that it is already combined by others. Consequently, they do not combine knowledge in an unique way, and the impact on the cohesiveness of the KS when these groups of applicants are removed is significantly lower. *Private Institutes* show a negative and significant coefficient. Therefore, they have a higher impact on the cohesiveness of the KS when removed, and to a larger extent, they combine knowledge in a unique way compared to others.

Other interesting results emerge when considering the interaction terms between the *Rank Degree Centrality* and the typology of applicant. This accounts for possible mitigation effects when the applicant holds a central position in the Regional Innovation Network. In other words, the interaction term tests how an increase of centrality in the "innovator network" affects the ability of different groups of applicants to combine knowledge. In this context, some groups of public organizations have a negative and significant coefficient. Looking more closely at the typology of the applicants, these are: *Max Planck Society*, *Universities*, *Technical Universities* and *Fraunhofer Institutes*. Public organizations have a considerable effect on the cohesiveness of the KS, and they combine unique knowledge only when they hold a central position in the Regional Innovation Network. Therefore, centrality acts as a positive force towards the combination of less-redundant technologies with a consequent higher impact on the cohesiveness of the KS. The results from a robustness check using a different main independent variable (namely: a ranking based on betweenness centrality, not on degree centrality) is provided in table 5.8 in Appendix 5.10. The results are similar to the ones presented here in the main analysis.

Table 5.6: Linear Model and Fixed Effects results

	Dependent variable:				
	Redundancy Coefficient				
	LM	LM	FE	FE	FE
	(1)	(2)	(3)	(4)	(5)
Type Max Planck	0.021	0.050	0.077	0.067	0.218***
	(0.051)	(0.050)	(0.048)	(0.047)	(0.079)
Type Leibniz	0.038	0.038	0.096*	0.087*	0.073
	(0.052)	(0.052)	(0.050)	(0.049)	(0.092)
Type Helmholtz	0.031	0.043	0.080	0.085	0.139
	(0.080)	(0.080)	(0.076)	(0.075)	(0.122)
Type University	0.091***	0.098***	0.098***	0.065***	0.203***
	(0.021)	(0.021)	(0.020)	(0.020)	(0.028)
Type Technical University	0.080***	0.088***	0.094***	0.071**	0.170***
	(0.031)	(0.031)	(0.029)	(0.029)	(0.043)
Type University of Applied Sciences	−0.019	−0.027	−0.019	−0.023	−0.025
	(0.043)	(0.042)	(0.040)	(0.040)	(0.069)
Type Fraunhofer	−0.023	0.011	0.066**	−0.019	0.187***
	(0.032)	(0.032)	(0.031)	(0.031)	(0.048)
Type Private Institutes	−0.171***	−0.159***	−0.141***	−0.131***	−0.082***
	(0.010)	(0.010)	(0.010)	(0.009)	(0.015)
log(Number of Patents)		−0.027***	−0.031***	−0.047***	−0.047***
		(0.002)	(0.002)	(0.002)	(0.002)
Rank Degree Centrality				0.616***	1.033***
				(0.031)	(0.080)
Degree Rank X Max Planck					−0.887***
					(0.333)
Degree Rank X Type Leibniz					−0.021
					(0.430)
Degree Rank X Type Helmholtz					−0.393
					(0.583)
Degree Rank X Type University					−0.821***
					(0.113)
Degree Rank X Type Technical Uni					−0.630***
					(0.178)
Degree Rank X Type University of Applied Sciences					0.016
					(0.402)
Degree Rank X Type Fraunhofer					−0.839***
					(0.131)
Degree Rank X Type Private Institutes					−0.345***
					(0.080)
Constant	0.676***	0.698***	0.534***	0.399***	0.649***
	(0.009)	(0.010)	(0.041)	(0.041)	(0.025)
Regional Dummies	No	No	Yes	Yes	Yes
Observations	14,780	14,780	14,780	14,780	14,780
R^2	0.037	0.045	0.149	0.172	0.176
Adjusted R^2	0.037	0.045	0.142	0.165	0.168
Residual Std. Error	0.355 (df = 14771)	0.353 (df = 14770)	0.335 (df = 14654)	0.331 (df = 14653)	0.330 (df = 14645)
F Statistic	71.672*** (df = 8; 14771)	77.757*** (df = 9; 14770)	20.523*** (df = 125; 14654)	24.095*** (df = 126; 14653)	23.341*** (df = 134; 14645)
Note:					*p<0.1; **p<0.05; ***p<0.01

5.8 Conclusion

Different organizations have different purposes based on their main focus (basic or applied research). They also combine knowledge in a different way. Basic research organizations are usually regarded as explorers. Whereas, applied research organizations are usually regarded as exploiters (Rowley et al., 2000; Hervas-Oliver et al., 2017; Miller et al., 2005). This divide can be reflected in the type of combinations developed by different entities. Since the development of new technological trajectories need diverse knowledge for their development (Castaldi et al., 2015; Arts and Veugelers, 2015), basic research organizations should combine knowledge differently with respect to others. However, the central position occupied by these basic research entities in the Regional Innovation Network could act as a driving force towards a more exploitative attitude (Gilsing, Nooteboom, Vanhaverbeke, Duysters, and Van Den Oord, 2008). Pursuing the development of new technological trajectories is risky and the fear of losing centrality could inhibit them (Hervas-Oliver et al., 2017). By contrast, the paper by Graf and Menter (2021) finds that basic research organizations occupying a central position in the RIN produce more radical patents. This finding suggests that these organizations combine different knowledge to produce such radical inventions through exploration activities. Complementing these previous studies on the effect of public and private organizations on the quality of inventions, I investigate the impact of different organizations on the type and uniqueness of knowledge combinations created.

To capture this effect, I introduce a new measure called a Redundancy Coefficient (RC), which estimates how many combinations inside the technological space of a region would survive when the patents of one applicant are removed. This measure shows how good an applicant is in combining knowledge that no one else is combining in the KS and therefore has a higher potential to develop new technological trajectories. Moreover, as demonstrated in the descriptive analysis, the lower is the redundancy of an applicant, the more it affects the cohesiveness of the technological space. However, the Redundancy Coefficient alone is not sufficient to assess the impact that applicants have on the uniqueness of combinations. RC and the effect that it has on the cohesiveness of the network is influenced by the number of patents that each applicant has, therefore it is necessary to employ an empirical approach to control for this problem.

Using an empirical approach which employs the aforementioned RC as the dependent variable and a set of dummies distinguishing between the different typologies of applications as the independent variable, I find that different organizations combine knowledge in different ways. In particular, public organizations like *universities*, *technical universities* and *Fraunhofer institutes*, to a larger extent, combine knowledge that is already combined by others, whereas *private institutes* combine unique knowledge. However, the results change when the typology of the applicant is considered with the mitigation effect of centrality inside the Regional Innovation Network. *Max Planck*, *Fraunhofer Institutes*, *universities*, *technical universities* and *private institutes* combine knowledge differently than others. In other words, these applicants combine technologies in an unique way when they are central. This finding suggests that not only does the typology of an applicant matter for the quality of technological combinations, but the centrality in the RIN is also a relevant factor.

These results suggest that policymakers should support basic research institutes in abandoning the ivory tower culture in favor of a more central role inside the Regional Innovation Network (Etzkowitz et al., 2000). This approach would help them actually combine technologies that are fundamental for the regional Knowledge Space. In this way, public organizations could create a solid knowledge base that through spillovers, which would allow knowledge to flow to other entities like private firms (Graf and Menter, 2021). Promoting further integration of applied and basic research should be pursued. However, policymakers should not forget that organizations can also work well in engaging different types of research. Consequently, every attempt to modify the agenda of these organizations could harm them. *Max Planck*, *universities*, *technical universities* and *Fraunhofer institutes* are able to combine technologies in an unique way when their centrality is high, whereas Helmholtz, Leibniz and university of applied sciences do not show any significance. However, this finding does not imply that the latter produces less important combinations but instead that they are involved in combining more marginal knowledge that could become mainstream in the future. Organizations on their own cannot trigger technological development in a region. Rather, it is the interaction and cooperation of all the interested actors that allows this process. Policymakers should take into account this interplay when shaping new cluster policies (Basilico et al., 2022).

The study proposed here has several limitations. First, when using only patents as database for the analysis, only patentable inventions are included. As a result, many non-patentable inventions (for example advances in software and services) are neglected (Griliches, 1990). Second, the analysis relies fully on the classification system of patents provided by patent offices. This implicitly implies that the patents classified in a single class are similar to each other. Patent offices classify patents for other purposes than the type of analysis proposed in this paper, therefore it might not hold true. Third, the Redundancy Coefficient is not yet diffused in evolutionary economic and economic geography studies. Hence, care should be taken in interpreting the results. Finally, these results may not be generalizable to other countries and research infrastructures other than the German one.

Based on the findings presented in this paper, future research should focus on exploring how diversification patterns of single organizations develop and how these patterns influence innovation and economic performance of regions. This research could be a fundamental step in determining the importance of organizations inside the Regional Innovation Network.

5.9 Correlation Tables

Table 5.7: Correlation table for the first regression with Redundancy Coefficient as dependent variable

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)
(1) Redundancy Coefficient	-	0.03***	0.03***	0.02***	0.10***	0.06***	0.02***	0.03***	-0.19***	-0.03***	-0.08***
(2) Type Max Planck		-	0.00	0.00	-0.01	-0.01	0.00	-0.01	-0.14***	0.00	0.02***
(3) Type Leibniz			-	0.00	-0.01	-0.01	0.00	-0.01	-0.13***	-0.01	0.02***
(4) Type Helmholtz				-	-0.01	0.00	0.00	0.00	-0.09***	0.00	0.00
(5) Type University					-	-0.02***	-0.01	-0.02***	-0.37***	-0.01	0.06***
(6) Type Technical University						-	-0.01	-0.01	-0.24***	-0.01	0.03***
(7) Type University of Applied Sciences							-	-0.01	-0.17***	-0.01	0.00
(8) Type Fraunhofer								-	-0.23***	0.03***	0.15***
(9) Type Firms									-	0.03***	-0.06***
(10) Number of Patents										-	0.22***
Note: *p ¡ 0.1; **p ¡ 0.05; ***p ¡ 0.01 (11) Rank Degree Centrality											-

5.10 Robustness checks

Table 5.8 shows the results for some robustness checks performed, using rank betweenness centrality instead of rank degree centrality. The model here is the same as the the one in table 5.6 for columns (4) and (5). The results for columns (1), (2) and (3) are not reported since they would be the same.

The results are not affected by the introduction of a different independent variable. When the dummies are interacted with the degree centrality the coefficient becomes negative for the same applicants as in table 5.6 (namely: Max Planck institutes, Universities, Technical Universities, Fraunhofer Institutes and Firms). However, the only significant results among the public organizations are universities and Fraunhofer institutes. This confirms that when considering a different centralization indicator as main independent variable the results do not change.

Table 5.8: Robustness checks results

	Dependent variable:	
	Redundancy Coefficient	
	FE	FE
	(1)	(2)
Type Max Planck	0.068	0.110
	(0.048)	(0.067)
Type Leibniz	0.094*	0.112
	(0.050)	(0.077)
Type Helmholtz	0.080	0.035
	(0.076)	(0.111)
Type University	0.087***	0.126***
	(0.020)	(0.025)
Type Technical University	0.084***	0.113***
	(0.029)	(0.038)
Type University of Applied Sciences	−0.018	−0.053
	(0.040)	(0.055)
Type Fraunhofer	0.032	0.100**
	(0.031)	(0.043)
Type Private Institutes	−0.139***	−0.123***
	(0.010)	(0.012)
log(Number of Patents)	−0.037***	−0.037***
	(0.003)	(0.003)
Rank Betweenness Centrality	0.227***	0.425***
	(0.034)	(0.079)
Betweenness Rank X Max Planck		−0.321
		(0.267)
Betweenness Rank X Type Leibniz		−0.179
		(0.446)
Betweenness Rank X Type Helmholtz		0.273
		(0.587)
Betweenness Rank X Type University		−0.324***
		(0.114)
Betweenness Rank X Type Technical Uni		−0.266
		(0.166)
Betweenness Rank X Type University of Applied Sciences		0.407
		(0.423)
Betweenness Rank X Type Fraunhofer		−0.349***
		(0.124)
Betweenness Rank X Type Private Institutes		−0.167**
		(0.077)
Constant	0.512***	0.717***
	(0.041)	(0.024)
Yes	Yes	
Observations	14,780	14,780
R^2	0.152	0.152
Adjusted R^2	0.144	0.145
Residual Std. Error	0.335 (df = 14653)	0.334 (df = 14645)
F Statistic	20.767*** (df = 126; 14653)	19.643*** (df = 134; 14645)
Note:		*p<0.1; **p<0.05; ***p<0.01

Chapter 6

Conclusion

The thesis contributes to the general understanding of the evolution of knowledge spaces, particularly on the role that important technologies have in this process. The research aims of the thesis are to define and understand the differences between different typologies of innovations that contribute to the technology evolution, to provide indicators to assess how technological spaces evolve and to analyse how drivers (both internal and external) can drive the process of technological evolution. In the core Chapters from 2 to 5, the evolution of technological spaces is analysed based on these three objectives.

In order to analyse how technology spaces evolve over time, the development of the thesis was an iterative process. The thesis recombines different streams of literature, different data sources and methodologies from different fields. In the following, I summarize the main findings and contributions, formulate policy implications and point out limitations and avenues for further research.

6.1 Main findings and contributions

Regarding the first research objective of the thesis, namely to distinguish and give a clear definition of different innovation concepts, Chapter 2 gives valuable insights. We performed a text analysis over 532 documents belonging to the category of the social sciences in Web of Science containing a definition of *radical*, *discontinuous*, *disruptive*, *breakthrough*, *continuous* and *incremental* innovations. Then, we assigned each phrase containing defining elements to one of the subsequent phases: *Requirements* (Input), *Features* (Content) or *Effects* (Output). Our broad results confirm the ones already put forward by Kovacs et al. (2019). The innovation labels can be clearly distinguished by the two dimensions *novelty* and *impact*. The "exceptional" innovations have higher degree of *novelty*, and they are more *impactful* whereas the "non-exceptional" innovations have a lower degree of *novelty* and they are less *impactful*. However, we identify two additional aspects often neglected by the relevant literature. On one hand, it is important to consider if the concepts are more market or technology related. On the other hand, it is important to understand on which level the resulting effects have a positive or a negative connotation (in other words if the labels are competence-enhancing or if they are competence-destroying). In the discussion of the innovation concepts, both of these dimensions has been rarely stressed, and in both cases, at our knowledge, they were never systematized. We find that the terms *disruptive* and *incremental* innovations are clearly related to the market-level whereas, *breakthrough* has a clear association with an impact on the technological level. *Disruptive* is clearly a competence-destroying concept while *incremental* is a competence-enhancing term. In this sense, we contribute to the scarce literature about the systematization of innovation terms by giving a more precise definition of the innovation labels.

Chapter 3 gives valuable insights on the second research objective of the thesis, namely to provide new indicators for assessing the importance of technologies inside knowledge spaces. Starting from the definition of well-known concepts like General Purpose Technologies and Key Enabling Technologies, we provide the definition of Bridging Technologies. These are technologies that in the context of knowledge spaces serve a bridging function by establishing direct and indirect links between other technology fields. We develop two definitions of bridging technologies, one based on the number of connections within the knowledge space and the other based on the structural position inside the knowledge space. Then, we develop two different indicators based on these definitions and we apply them on the Jena knowledge space to assess its evolution over time. We find that there are technologies emerging as bridging and others leaving this role, confirming our assumption that knowledge spaces are continuously evolving. Moreover, we introduced a new indicator called Revealed Bridging Advantage (RBA) for inter-regional comparisons. Our results show that large patenting regions are not necessarily the ones that embed most new technologies in their knowledge space and that the German knowledge space became less dependent on important technologies like transport, machinery and chemicals over time. Therefore, we contribute to the scarce literature of bridging technologies and knowledge spaces both from a theoretical and methodological point of view. The tools developed in this Chapter are implemented in the subsequent ones to assess how drivers are reshaping the development of knowledge spaces.

Chapters 4 and 5 deal with the last research objective of the thesis, namely to show how external and internal drivers reshape the development of knowledge spaces. Chapter 4 analyses how technology-based regional knowledge spaces are shaped by the introduction of a cluster policy. In particular, we analysed how the embeddedness of a specific targeted technology (biotechnology) by the BioRegio program is changing over time in the supported regions. We argue that the supported field should become more relevant in the knowledge space by creating new connections with other fields. From the empirical analysis performed using as dependent variable the betweenness centrality indicator and a difference-in-difference analysis, we observe a positive effect of the policy on the embeddedness of biotechnology after the funding ceases. Our analysis complements other evaluations of the BioRegio program (Engel et al., 2013; Graf and Broekel, 2020) which find only short time effects on innovation outputs and actor network structures. Our findings show that the direction of the exploration process (searching new ways to combine other technologies with biotechnology) is driven by policies. On a more general point of view, we demonstrate that the changes in knowledge spaces are driven by external factors (in this case public funding).

Chapter 5 deals with internal drivers of change in knowledge spaces, in particular, on how organizations present locally combine technologies important for the cohesiveness of the knowledge space. To perform such analysis, I introduced an indicator called Redundancy Coefficient that measures the extent to which an organization combines technologies in a different way than others. Not all organizations present locally are homogeneous. Therefore, I have divided them in different categories based on their research orientation. Moreover, I assess how central these organizations are in the regional innovation network. Both these forces can influence their propensity to combine technologies important for the cohesiveness of the knowledge space. Results show that when the centrality in the regional innovation system is not taken into account, only organizations that do mostly applied research are the ones combining knowledge in a different way than others. Interestingly, when the centrality in the regional innovation system is taken into account, public organizations also have an important role in knowledge recombination. This Chapter contributes to the scarce literature about the role of organizations in knowledge recombination activities, providing new insights and tools to measure it.

The findings of the thesis range from contributions to better define and generalize innovation activities, to the definition and identification of important technologies inside regional knowledge spaces providing tools to assess their impact and to an empirical contribution about which the possible internal and external drivers reshape the evolution of knowledge spaces.

6.2 Policy Implications

Concerning policy implications, the thesis offers insights based on different dimensions.

First, the differentiation of innovation labels between technological and marketed and the direction of their effects between competence-enhancing and competence-destroying is relevant for the policy implications. Whether the observed effects from innovation activities make a difference for the market or for the technology can shape the policy intervention. If the effect of innovation activities is specific to one of these two dimensions, a one-sizes-fits-all policies can be less effective rather than a targeted policy intervention.

Second, an assessment on the effects that targeted cluster policies have on the regional technological structures helps in the understanding of whether the objectives of such policy measures have been reached. In fact, cluster policies are usually targeted to organizations active in specific technologies with the intent to increase cross-fertilization activities with other, non-related, technologies. Therefore, such studies on the positive effects of policies on technological spaces can create room for an increase in funding for subsequent policy interventions.

Third, policy makers when introducing a new policy should also consider the effects that this could have on the technological structure of the targeted area based on their previous technological strengths. On one hand, negative effects could emerge when a policy is targeting regions that are already strong in a single technology. This would result in a technological reinforcement of such regions with an increase in the gap with the lagging ones. Therefore, the result is not beneficial in terms of equality. On the other hand, a massive investment in lagging regions could possibly result in a waste of resources. The technological strength of these regions is low, and the possibilities of cross-fertilization are scarce. Thus, in these cases it is difficult to build "cathedrals in the desert". Policy makers should target policies to hit weak spots in the knowledge spaces only when there is potential to actually reinforce them through cross-fertilization activities. When it is difficult to promote such activities, the investment could result in a waste of resources.

Fourth, the main results on the organizations involved locally in the process of production of knowledge suggest that policy makers should pay attention on the positioning of such actors inside the region. In fact, especially for public research institutes, it has been demonstrated that when these organizations are central in the regional innovation network, they combine core knowledge for the region. Thus, policy makers should support these organizations through the promotion of knowledge transfer activities with other partners inside the regional innovation network. In this case, the organizations would benefit from a varied asset of knowledge sources, and they would contribute to a higher extent to reinforce the knowledge regional base.

6.3 Limitations and further research avenues

This thesis certainly contributes to the scarce literature regarding the study of the evolution of technological spaces and on the identification of innovative activities. However, the research efforts are not exempt from a certain amount of limitations, including directions and alternative paths that have not been undertaken.

In particular, in Chapter 2 where we characterized different innovation terms, we based our analysis only on a subset of most famous concepts in innovation literature. It is possible to extend such analysis including other emerging terms (like *architectural* innovation) to provide researchers and practitioners with a more comprehensive distinction among different innovation definitions. Moreover, another aspect that has been neglected is the connection between the indicators developed for assessing the impact of specific innovations and the innovation terms itself. Finally, the historical evolution of these labels has not been taken into account. We have treated all the innovation labels as if they do not change over time. This is far from true, as every author when using these definitions adds some features and changes slightly the meaning of each term. An evolutionary perspective gives insights on why and how nowadays specific terms are used to relay a specific meaning.

The main limitation of Chapters 3 to 5 is that only the effects on the technological structure of regions have been addressed. Future research should focus on how these changes induced by organizations, policies and prominent technologies influence the future economic and innovative performance of the region. This type of research pushes the frontier much further, and it would disentangle the inter-dependencies between the changes on the technological level and on the economic sphere. The changes on the technological level could eventually also result in a lower economic performance in the region since it has to adapt to the different setting. However, once the region and the actors composing it adequately adapt to the change, the region could face economic growth.

There are two general technical limitations common for Chapters 3 to 5. These are the usage of patent data as the main source for the analysis and the fact that most of the analysis relies on the classification system of patents. First, only patentable inventions are included in the analysis neglecting all the non-patentable inventions. Therefore, the chapters are based only on a part of the regional technological spaces. One of the challenges undertaken by recent papers (e.g. Balland and Boschma, 2021) studying knowledge spaces is to connect different data sources to include a wider spectrum of regional capabilities. This process bears multiple obstacles because the connection between different databases is not straightforward, and concordance tables must be used in order to perform such analyses. Second, the usage of the classification system of patents implies that a patent classified in a class is substantially different from a patent classified in another class. This might be far from true because the classification done by the patent offices is for other reasons other than for the construction of a knowledge space. Nowadays, more sophisticated techniques using, for example, text analysis have been put forward by researchers to overcome this problem. However, they require high performance computers and an assessment by a commission of experts. Therefore, these type of analyses are, for now, suitable for a small number of regions or for a limited amount of technological classes.

In conclusion, the thesis has highlighted how technology spaces change over time and the factors that drive these processes. While this analysis bears multiple challenges that could not be faced uniquely in this dissertation, I hope that the contribution adds to understanding the dynamics of technological spaces and inspires subsequent research in that direction.

Bibliography

Abernathy, W. & Clark, K. (1985). Innovation: Mapping the winds of creative destruction. *Research Policy*, *14*(1), 3–22.

Acharya, V. V., Hasan, I., & Saunders, A. (2006). Should banks be diversified? Evidence from individual bank loan portfolios. *The Journal of Business*, *79*(3), 1355–1412.

Acs, Z. J., Anselin, L., & Varga, A. (2002). Patents and innovation counts as measures of regional production of new knowledge. *Research policy*, *31*(7), 1069–1085.

Acs, Z. J., Braunerhjelm, P., Audretsch, D. B., & Carlsson, B. (2009). The knowledge spillover theory of entrepreneurship. *Small business economics*, *32*(1), 15–30.

Ahuja, G. & Lampert, C. M. (2001). Entrepreneurship in the large corporation: a longitudinal study of how established firms create breakthrough inventions. *Strategic management journal*, *22*(6-7), 521–543.

Akyildiz, I. F., Nie, S., Lin, S.-C., & Chandrasekaran, M. (2016). 5G roadmap: 10 key enabling technologies. *Computer Networks*, *106*, 17–48.

Alstott, J., Triulzi, G., Yan, B., & Luo, J. (2017). Mapping technology space by normalizing patent networks. *Scientometrics*, *110*(1), 443–479.

Andersson, M. & Karlsson, C. (2006). Regional innovation systems in small and medium-sized regions. In *The emerging digital economy: entrepreneurship, clusters, and policy* (pp. 55–81). Springer Berlin Heidelberg.

Ansari, S., Garud, R., & Kumaraswamy, A. (2016). The disruptor's dilemma: TiVo and the US television ecosystem. *Strategic Management Journal*, *37*(9), 1829–1853.

Arthur, W. B. (2009). *The nature of technology: What it is and how it evolves*. Simon and Schuster.

Arts, S. (2012). Path dependency and recombinant exploration: how established firms can outperform in the creation of technological breakthroughs. *FEB Research Report MSI_1228*.

Arts, S., Appio, F. P., & Van Looy, B. (2013). Inventions shaping technological trajectories: do existing patent indicators provide a comprehensive picture? *Scientometrics*, *97*(2), 397–419.

Arts, S., Cassiman, B., & Gomez, J. C. (2018). Text matching to measure patent similarity. *Strategic Management Journal*, *39*(1), 62–84.

Arts, S. & Veugelers, R. (2015). Technology familiarity, recombinant novelty, and breakthrough invention. *Industrial and Corporate Change*, *24*(6), 1215–1246.

Audretsch, D. B. & Feldman, M. P. (1996). Innovative clusters and the industry life cycle. *Review of Industrial Organization*, *11*(2), 253–273.

Audretsch, D., Fornahl, D., & Klarl, T. (2022). Radical innovation and its regional impact—a roadmap for future research. *Small Business Economics*, *58*, 1153–1156.

Ayres, R. U. (1988). Barriers and breakthroughs: an "expanding frontiers" model of the technology-industry life cycle. *Technovation*, *7*(2), 87–115.

Balland, P.-A. & Boschma, R. (2021). *Do scientific capabilities in specific domains matter for technological diversification in european regions?* Utrecht University, Department of Human Geography and Spatial Planning.

Balland, P.-A., Boschma, R., Crespo, J., & Rigby, D. L. (2019). Smart specialization policy in the European Union: relatedness, knowledge complexity and regional diversification. *Regional Studies*, *53*(9), 1252–1268.

Balland, P.-A. & Rigby, D. (2017). The geography of complex knowledge. *Economic Geography*, *93*(1), 1–23.

Balland, P.-A., Rigby, D., & Boschma, R. (2015). The technological resilience of US cities. *Cambridge Journal of Regions, Economy and Society*, *8*(2), 167–184.

Baptista, R. & Swann, P. (1998). Do firms in clusters innovate more? *Research Policy*, *27*(5), 525–540.

Basilico, S., Cantner, U., & Graf, H. (2022). Policy influence in the knowledge space: a regional application. *The Journal of Technology Transfer*.

Basilico, S. & Graf, H. (2020). *Bridging technologies in the regional knowledge space: measurement, evolution and determinants* (Working Paper No. 12). Friedrich Schiller University Jena.

Beaudry, C. & Breschi, S. (2003). Are firms in clusters really more innovative? *Economics of Innovation and New Technology*, *12*(4), 325–342.

Belleflamme, P., Picard, P., & Thisse, J. F. (2000). An Economic Theory of Regional Clusters. *Journal of Urban Economics*, *48*(1), 158–184.

Benner, M. J. & Tushman, M. (2002). Process management and technological innovation: a longitudinal study of the photography and paint industries. *Administrative science quarterly*, *47*(4), 676–707.

Berends, H., Vanhaverbeke, W., & Kirschbaum, R. (2007). Knowledge management challenges in new business development: case study observations. *Journal of engineering and technology management*, *24*(4), 314–328.

Bergek, A., Berggren, C., Magnusson, T., & Hobday, M. (2013). Technological discontinuities and the challenge for incumbent firms: destruction, disruption or creative accumulation? *Research Policy*, *42*(6-7), 1210–1224.

Birkinshaw, J., Bessant, J., & Delbridge, R. (2007). Finding, forming, and performing: creating networks for discontinuous innovation. *California management review*, *49*(3), 67–84.

BMBF. (2012). *Federal report on research and innovation.* Federal Ministry of Education and Research.

BMBF. (2014). *Federal report on research and innovation.* Federal Ministry of Education and Research.

BMBF. (2020). *Federal report on research and innovation.* Federal Ministry of Education and Research.

BMBF. (2017). *The german research landscape.* Federal Ministry of Education and Research.

Boer, H. & Gertsen, F. (2003). From continuous improvement to continuous innovation: a (retro)(per) spective. *International Journal of Technology Management*, *26*(8), 805–827.

Boschma, R. (2005). Proximity and innovation: a critical assessment. *Regional studies*, *39*(1), 61–74.

Boschma, R. (2017). Relatedness as driver of regional diversification: a research agenda. *Regional Studies*, *51*(3), 351–364.

Boschma, R. (2015). Towards an Evolutionary Perspective on Regional Resilience. *Regional Studies*, *49*(5), 733–751.

Boschma, R. A. & Lambooy, J. G. (1999). Evolutionary economics and economic geography. *Journal of evolutionary economics*, *9*, 411–429.

Boschma, R. A. & ter Wal, A. L. J. (2007). Knowledge networks and innovative performance in an industrial district: the case of a footwear district in the south of italy. *Industry and Innovation*, *14*(2), 177–199.

Boschma, R., Balland, P.-A., & Kogler, D. F. (2014). Relatedness and technological change in cities: the rise and fall of technological knowledge in US metropolitan areas from 1981 to 2010. *Industrial and corporate change*, *24*(1), 223–250.

Boschma, R. & Iammarino, S. (2009). Related variety, trade linkages, and regional growth in Italy. *Economic geography*, *85*(3), 289–311.

Boschma, R., Minondo, A., & Navarro, M. (2012). Related variety and regional growth in Spain. *Papers in Regional Science*, *91*(2), 241–256.

Boschma, R., Minondo, A., & Navarro, M. (2013). The emergence of new industries at the regional level in Spain: a proximity approach based on product relatedness. *Economic geography*, *89*(1), 29–51.

Bower, J. L. & Christensen, C. M. (1995). *Disruptive technologies: catching the wave*. Harvard Business Review.

Breschi, S. & Lenzi, C. (2016). Co-invention networks and inventive productivity in US cities. *Journal of Urban Economics*, *92*, 66–75.

Breschi, S. & Lissoni, F. (2009). Mobility of skilled workers and co-invention networks: an anatomy of localized knowledge flows. *Journal of economic geography*, *9*(4), 439–468.

Breschi, S., Lissoni, F., & Malerba, F. (2003). Knowledge-relatedness in firm technological diversification. *Research policy*, *32*(1), 69–87.

Bresnahan, T. F. (2010). General Purpose Technologies. In *Handbook of the economics of innovation* (Vol. 2, pp. 761–791). Elsevier.

Bresnahan, T. F. (1986). Measuring the spillovers from technical advance: mainframe computers in financial services. *The American Economic Review*, 742–755.

Bresnahan, T. F. & Trajtenberg, M. (1995). General purpose technologies 'engines of growth'? *Journal of econometrics*, *65*(1), 83–108.

Broekel, T. (2012). Collaboration intensity and regional innovation efficiency in germany—a conditional efficiency approach. *Industry and Innovation*, *19*(2), 155–179.

Broekel, T. (2019). Using structural diversity to measure the complexity of technologies. *PloS one*, *14*(5).

Broekel, T., Fornahl, D., & Morrison, A. (2015). Another cluster premium: innovation subsidies and R&D collaboration networks. *Research policy*, *44*(8), 1431–1444.

Broekel, T. & Graf, H. (2012). Public research intensity and the structure of german R&D networks: a comparison of 10 technologies. *Economics of Innovation and New Technology*, *21*(4), 345–372.

Büschgens, T., Bausch, A., & Balkin, D. B. (2013). Organizing for radical innovation—a multi-level behavioral approach. *The Journal of High Technology Management Research*, *24*(2), 138–152.

Cantner, U. & Graf, H. (2006). The network of innovators in Jena: An application of social network analysis. *Research Policy*, *35*(4), 463–480.

Cantner, U., Meder, A., & Wolf, T. (2011). Success and failure of firms' innovation co-operations: the role of intermediaries and reciprocity. *Papers in Regional Science*, *90*(2), 313–329.

Cantner, U. & Vannuccini, S. (2018). Elements of a schumpeterian catalytic research and innovation policy. *Industrial and Corporate Change*, *27*(5), 833–850.

Cantner, U. & Vannuccini, S. (2017). Pervasive technologies and industrial linkages: modeling acquired purposes. *Structural Change and Economic Dynamics*.

Carlsson, B. & Stankiewicz, R. (1991). On the nature, function and composition of technological systems. *Journal of Evolutionary Economics*, *1*(2), 93–118.

Castaldi, C., Frenken, K., & Los, B. (2015). Related variety, unrelated variety and technological breakthroughs: an analysis of us state-level patenting. *Regional studies*, *49*(5), 767–781.

Champenois, C. (2012). How can a cluster policy enhance entrepreneurship? Evidence from the German 'BioRegio' case. *Environment and Planning C: Government and Policy*, *30*(5), 796–815.

Christensen, C. M., Johnson, M. W., & Rigby, D. K. (2002). Foundations for growth: how to identify and build disruptive new businesses. *MIT Sloan Management Review*, *43*(3), 22.

Cohendet, P. & Llerena, P. (1997). Learning, technical change and public policy: how to create and exploit diversity. *Edquist, C., Systems of innovation, Pinter, London and Washington*, 223–241.

Colombo, M. G., Franzoni, C., & Veugelers, R. (2015). Going radical: producing and transferring disruptive innovation. *The Journal of Technology Transfer*, *40*(4), 663–669.

Cooke, P. (2001). New economy innovation systems: biotechnology in europe and the USA. *Industry and Innovation*, *8*(3), 267–289.

Cooper, L. G. (2000). Strategic marketing planning for radically new products. *Journal of marketing*, *64*(1), 1–16.

Corradini, C. & De Propris, L. (2017). Beyond local search: bridging platforms and inter-sectoral technological integration. *Research Policy*, *46*(1), 196–206.

Csardi, G. & Nepusz, T. (2006). The igraph software package for complex network research. *InterJournal*, *Complex Systems*.

Dahlin, K. B. & Behrens, D. M. (2005). When is an invention really radical?: defining and measuring technological radicalness. *Research Policy*, *34*(5), 717–737.

Delgado, M., Porter, M. E., & Stern, S. (2014). Clusters, convergence, and economic performance. *Research Policy*, *43*(10), 1785–1799.

Della Malva, A. & Riccaboni, M. (2015). *(un) conventionality in combinations: at the origins of breakthrough inventions.* Academy of Management Briarcliff Manor.

Dewar, R. D. & Dutton, J. E. (1986). The adoption of radical and incremental innovations: an empirical analysis. *Management science*, *32*(11), 1422–1433.

Dijk, M., Wells, P., & Kemp, R. (2016). Will the momentum of the electric car last? testing an hypothesis on disruptive innovation. *Technological Forecasting and Social Change*, *105*, 77–88.

Dohse, D. (2000). Technology policy and the regions—the case of the BioRegio contest. *Research Policy*, *29*(9), 1111–1133.

Dohse, D. & Staehler, T. (2008). *Bioregio, Bioprofile and the rise of the German biotech industry* (Kiel Working Paper No. 1456). Kiel Institute for the World Economy.

Dosi, G. (1982). Technological paradigms and technological trajectories. A suggested interpretation of the determinants and directions of technical change. *Research Policy*, *11*(3), 147–162.

Dosi, G. (1988). The nature of the innovative process. *Technical change and economic theory*.

Dosi, G. & Nelson, R. R. (2010). Technical change and industrial dynamics as evolutionary processes. *Handbook of the Economics of Innovation*, *1*, 51–127.

Downs Jr, G. W. & Mohr, L. B. (1976). Conceptual issues in the study of innovation. *Administrative science quarterly*, 700–714.

Duranton, G. (2011). California Dreamin': The Feeble Case for Cluster Policies. *Review of Economic Analysis*, *3*(1), 3–45.

Duranton, G. & Puga, D. (2000). Diversity and specialisation in cities: why, where and when does it matter? *Urban Studies*, *37*(3), 533–555.

EFI. (2017). *Report on research, innovation and technological performance in Germany 2017*. Berlin: EFI - Commission of Experts for Research and Innovation.

Eickelpasch, A. & Fritsch, M. (2005). Contests for cooperation - A new approach in German innovation policy. *Research Policy*, *34*(8), 1269–1282.

Engel, D. & Heneric, O. (2008). Legal frameworks and public support in the biotechnology industry. In H. Patzelt & T. Brenner (Eds.), *Handbook of bioentrepreneurship* (pp. 249–274). New York: Springer US.

Engel, D., Mitze, T., Patuelli, R., & Reinkowski, J. (2013). Does Cluster Policy Trigger R&D Activity? Evidence from German Biotech Contests. *European Planning Studies*, *21*(11), 1735–1759.

Ettlie, J. E., Bridges, W. P., & O'keefe, R. D. (1984). Organization strategy and structural differences for radical versus incremental innovation. *Management science*, *30*(6), 682–695.

Etzkowitz, H. (2004). The evolution of the entrepreneurial university. *International Journal of Technology and Globalisation*, *1*(1), 64–77.

Etzkowitz, H., Webster, A., Gebhardt, C., & Terra, B. R. C. (2000). The future of the university and the university of the future: evolution of ivory tower to entrepreneurial paradigm. *Research policy*, *29*(2), 313–330.

European Commission. (2009). Preparing for our future: developing a common strategy for key enabling technologies in the EU. European Commission Brussels, Belgium.

European Commission. (2003). *Third European Report on Science & Technology Indicators: Towards a Knowledge-based Economy.* Office for Official Publications of the European Communities.

Fagerberg, J., Verspagen, B., & Caniels, M. (1997). Technology, growth and unemployment across european regions. *Regional Studies*, *31*(5), 457–466.

Fleming, L. & Sorenson, O. (2001). Technology as a complex adaptive system: evidence from patent data. *Research policy*, *30*(7), 1019–1039.

Forés, B. & Camisón, C. (2016). Does incremental and radical innovation performance depend on different types of knowledge accumulation capabilities and organizational size? *Journal of business research*, *69*(2), 831–848.

Fornahl, D., Broekel, T., & Boschma, R. (2011). What drives patent performance of German biotech firms? The impact of R&D subsidies, knowledge networks and their location. *Papers in Regional Science*, *90*(2), 395–418.

Freeman, L. C. (1978). Centrality in social networks conceptual clarification. *Social Networks*, *1*(3), 215–239.

Frenken, K., Van Oort, F., & Verburg, T. (2007). Related variety, unrelated variety and regional economic growth. *Regional studies*, *41*(5), 685–697.

Fritsch, M. & Franke, G. (2004). Innovation, regional knowledge spillovers and R&D cooperation. *Research policy*, *33*(2), 245–255.

Fritsch, M. & Graf, H. (2010). *How national conditions affect regional innovation systems – the case of the two Germanys* (Jena Economic Research Papers No. 2010-054). Friedrich-Schiller-University Jena, Max-Planck-Institute of Economics.

Garcia, R. & Calantone, R. (2002). A critical look at technological innovation typology and innovativeness terminology: a literature review. *Journal of Product Innovation Management*, *19*(2), 110–132.

Gatignon, H., Tushman, M. L., Smith, W., & Anderson, P. (2002). A structural approach to assessing innovation: construct development of innovation locus, type, and characteristics. *Management science*, *48*(9), 1103–1122.

Gilbert, B. A. & Campbell, J. T. (2015). The geographic origins of radical technological paradigms: a configurational study. *Research Policy*, *44*(2), 311–327.

Gilsing, V., Nooteboom, B., Vanhaverbeke, W., Duysters, G., & Van Den Oord, A. (2008). Network embeddedness and the exploration of novel technologies: technological distance, betweenness centrality and density. *Research policy*, *37*(10), 1717–1731.

Giuliani, E. & Bell, M. (2008). Industrial clusters and the evolution of their knowledge networks: revisiting a Chilean case. *IV Globelics Conference*, *44*(2005), 1–25.

Giuliani, E. & Bell, M. (2005). The micro-determinants of meso-level learning and innovation: Evidence from a Chilean wine cluster. *Research Policy*, *34*(1), 47–68.

Giuliani, E., Matta, A., & Pietrobelli, C. (2016). Networks, cluster development programs, and performance: the electronics cluster in Córdoba, Argentina. *The Impact Evaluation of Cluster Development Programs: Methods and Practices*, 117–150.

Glaeser, E. L., Kallal, H. D., Scheinkman, J. A., & Shleifer, A. (1992). Growth in cities. *Journal of Political Economy*, *100*(6), 1126–1152.

Gopalakrishnan, S. & Damanpour, F. (1997). A review of innovation research in economics, sociology and technology management. *Omega*, *25*(1), 15–28.

Govindarajan, V., Kopalle, P. K., & Danneels, E. (2011). The effects of mainstream and emerging customer orientations on radical and disruptive innovations. *Journal of Product Innovation Management*, *28*, 121–132.

Graf, H. (2012). Inventor networks in emerging key technologies: information technology vs. semiconductors. *Journal of Evolutionary Economics*, *22*(3), 459–480.

Graf, H. (2006). *Networks in the innovation process: local and regional interactions*. Cheltenham, UK: Edward Elgar.

Graf, H. (2017). *Regional innovator networks: a review and an application with R*. Jena Economic Research Papers.

Graf, H. & Broekel, T. (2020). A shot in the dark? Policy influence on cluster networks. *Research Policy*, *49*(3), 103920.

Graf, H. & Henning, T. (2009). Public research in regional networks of innovators: A comparative study of Four East German regions. *Regional Studies*, *43*(10), 1349–1368.

Graf, H. & Krüger, J. J. (2011). The performance of gatekeepers in innovator networks. *Industry and Innovation*, *18*(1), 69–88.

Graf, H. & Menter, M. (2021). Public research and the quality of inventions: the role and impact of entrepreneurial universities and regional network embeddedness. *Small Business Economics*, *58*, 1187–1204.

Green, S. G., Gavin, M. B., & Aiman-Smith, L. (1995). Assessing a multidimensional measure of radical technological innovation. *IEEE transactions on engineering management*, *42*(3), 203–214.

Griliches, Z. (1990). Patent statistics as economic indicators: a survey. *Journal of Economic Literature*, *28*(4), 1661.

Griliches, Z. (1992). The search for R&D spillovers. *The Scandinavian Journal of Economics*, S29–S47.

Hall, B. H. & Trajtenberg, M. (2004). *Uncovering GPTs with patent data.* National Bureau of Economic Research.

Hansen, M. T. (1999). The search-transfer problem: the role of weak ties in sharing knowledge across organization subunits. *Administrative science quarterly*, *44*(1), 82–111.

Hao, B. & Feng, Y. (2016). How networks influence radical innovation: the effects of heterogeneity of network ties and crowding out. *Journal of Business & Industrial Marketing*.

Hausmann, R. & Hidalgo, C. A. (2011). The network structure of economic output. *Journal of Economic Growth*, *16*(4), 309–342.

Hausmann, R. & Klinger, B. (2007). The structure of the product space and the evolution of comparative advantage. *CID Working Paper Series*.

Henderson, R. (1993). Underinvestment and incompetence as responses to radical innovation: evidence from the photolithographic alignment equipment industry. *The RAND Journal of Economics*, 248–270.

Henderson, R. M. & Clark, K. B. (1990). Architectural innovation: the reconfiguration of existing product technologies and the failure of established firms. *Administrative science quarterly*, 9–30.

Henkel, J., Rønde, T., & Wagner, M. (2015). And the winner is—acquired. entrepreneurship as a contest yielding radical innovations. *Research Policy*, *44*(2), 295–310.

Hervás-Oliver, J.-L., Albors-Garrigos, J., Estelles-Miguel, S., & Boronat-Moll, C. (2018). Radical innovation in marshallian industrial districts. *Regional Studies*, *52*(10), 1388–1397.

Hervas-Oliver, J.-L., Lleo, M., & Cervello, R. (2017). The dynamics of cluster entrepreneurship: knowledge legacy from parents or agglomeration effects? the case of the castellon ceramic tile district. *Research Policy*, *46*(1), 73–92.

Hidalgo, C. A. & Hausmann, R. (2009). The building blocks of economic complexity. *Proceedings of the national academy of sciences*, *106*(26), 10570–10575.

Hidalgo, C. A., Klinger, B., Barabasi, A.-L., & Hausmann, R. (2007). The product space conditions the development of nations. *Science*, *317*(5837), 482–487.

Hill, C. W. & Rothaermel, F. T. (2003). The performance of incumbent firms in the face of radical technological innovation. *Academy of management review*, *28*(2), 257–274.

Hospers, G.-J. & Beugelsdijk, S. (2002). Regional cluster policies: learning by comparing? *Kyklos*, *55*(3), 381–402.

Jaffe, A. B. (1989). Characterizing the "technological position" of firms, with application to quantifying technological opportunity and research spillovers. *Research Policy*, *18*(2), 87–97.

Jaffe, A. B., Trajtenberg, M., & Henderson, R. (1993). Geographic localization of knowledge spillovers as evidenced by patent citations. *the Quarterly journal of Economics*, *108*(3), 577–598.

Joo, S. H. & Kim, Y. (2010). Measuring relatedness between technological fields. *Scientometrics*, *83*(2), 435–454.

Kaiser, R. & Prange, H. (2004). The reconfiguration of National Innovation Systems - The example of German biotechnology. *Research Policy*, *33*(3), 395–408.

Kaplan, S. & Vakili, K. (2015). The double-edged sword of recombination in breakthrough innovation. *Strategic Management Journal*, *36*(10), 1435–1457.

Kaplan, S. M. (1999). Discontinuous innovation and the growth paradox. *Strategy & leadership*.

Kassicieh, S. K., Kirchhoff, B. A., Walsh, S. T., & McWhorter, P. J. (2002). The role of small firms in the transfer of disruptive technologies. *Technovation*, *22*(11), 667–674.

Kattel, R. & Mazzucato, M. (2018). Mission-oriented innovation policy and dynamic capabilities in the public sector. *Industrial and Corporate Change*, *27*(5), 787–801.

Kay, L., Newman, N., Youtie, J., Porter, A. L., & Rafols, I. (2014). Patent Overlay Mapping: Visualizing Technological Distance. *Journal of the Association for Information Science and Technology*, *65*(12), 2432–2443.

Kemp, R. (1994). Technology and the transition to environmental sustainability: the problem of technological regime shifts. *Futures*, *26*(10), 1023–1046.

Khan, M. & Dernis, H. (2006). Global overview of innovative activities from the patent indicators perspective. Organisation for Economic Co-Operation and Development (OECD).

Kiese, M. (2019). Regional cluster policies in Germany: challenges, impacts and evaluation practices. *Journal of Technology Transfer*, *44*(6), 1698–1719.

Kim, D., Cerigo, D. B., Jeong, H., & Youn, H. (2016). Technological novelty profile and invention's future impact. *EPJ Data Science*, *5*(1), 1–15.

Kogler, D. F., Rigby, D. L., & Tucker, I. (2013). Mapping knowledge space and technological relatedness in US cities. *European Planning Studies*, *21*(9), 1374–1391.

Koo, J. (2005). Technology spillovers, agglomeration, and regional economic development. *Journal of Planning Literature*, *20*(2), 99–115.

Kostoff, R. N., Boylan, R., & Simons, G. R. (2004). Disruptive technology roadmaps. *Technological Forecasting and Social Change*, *71*(1-2), 141–159.

Kovacs, A., Marullo, C., Verhoeven, D., & Van Looy, B. (2019). *Radical, disruptive, discontinuous and breakthrough innovation: more of the same?* Academy of Management Briarcliff Manor, NY 10510.

Krauss, G. & Stahlecker, T. (2001). New Biotechnology Firms in Germany: Heidelberg and the BioRegion Rhine-Neckar Triangle. *Small Business Economics*, *17*(1-2), 143–153.

Landes, D. S. (1969). *The Unbound Prometheus: Technological Change and Industrial Development in Western Europe from 1750 to the Present* (2nd ed.). Cambridge University Press.

Latapy, M., Magnien, C., & Del Vecchio, N. (2008). Basic notions for the analysis of large two-mode networks. *Social networks*, *30*(1), 31–48.

Lettl, C. (2007). User involvement competence for radical innovation. *Journal of engineering and technology management*, *24*(1-2), 53–75.

Lettl, C., Herstatt, C., & Gemuenden, H. G. (2006). Users' contributions to radical innovation: evidence from four cases in the field of medical equipment technology. *R&D Management*, *36*(3), 251–272.

Leyden, D. P. & Menter, M. (2018). The legacy and promise of vannevar bush: rethinking the model of innovation and the role of public policy. *Economics of Innovation and New Technology*, *27*(3), 225–242.

Leydesdorff, L., Kogler, D. F., & Yan, B. (2017). Mapping patent classifications: portfolio and statistical analysis, and the comparison of strengths and weaknesses. *Scientometrics*, *112*(3), 1573–1591.

Leydesdorff, L., Kushnir, D., & Rafols, I. (2014). Interactive overlay maps for US patent (USPTO) data based on International Patent Classification (IPC). *Scientometrics*, *98*, 1583–1599.

Linton, J. D. (2009). De-babelizing the language of innovation. *Technovation*, *29*(11), 729–737.

Lucena-Piquero, D. & Vicente, J. (2019). The visible hand of cluster policy makers: an analysis of aerospace valley (2006-2015) using a place-based network methodology. *Research Policy*, *48*(3), 830–842.

Lundvall, B.-A. (2016). From the economics of knowledge to the learning economy. *The Learning Economy and the Economics of Hope*, 133.

Lynn, G. S., Morone, J. G., & Paulson, A. S. (1996). Marketing and discontinuous innovation: the probe and learn process. *California management review*, *38*(3), 8–37.

Malerba, F. & Orsenigo, L. (1997). Technological Regimes and Sectoral Patterns of Innovative Activities. *Industrial and Corporate Change*, *6*(1), 83–118.

Malmberg, A. & Maskell, P. (1997). Towards an explanation of regional specialization and industry agglomeration. *European planning studies*, *5*(1), 25–41.

Mar, M. & Massard, N. (2021). Animate the cluster or subsidize collaborative R&D? A multiple overlapping treatments approach to assess the impacts of the French cluster policy. *Industrial and Corporate Change*.

Markides, C. (2006). Disruptive innovation: in need of better theory. *Journal of product innovation management*, *23*(1), 19–25.

Markusen, A. (1996). Sticky places in slippery space: a typology of industrial districts. *Economic Geography*, *72*(3), 293–313.

Marshall, A. (1890). *Principles of Economics*. London: Macmillan.

Martin, R. & Sunley, P. (1996). Paul Krugman's geographical economics and its implications for regional development theory: A critical assessment. *Economic Geography*, *72*(3), 259–292.

Martin, R. & Sunley, P. (2003). Deconstructing clusters: Chaotic concept or policy panacea? *Journal of Economic Geography*, *3*(1), 5–35.

Maskell, P. (2001). Towards a knowledge-based theory of the geographical cluster. *Industrial and corporate change*, *10*(4), 921–943.

Mewes, L. (2019). Scaling of atypical knowledge combinations in american metropolitan areas from 1836 to 2010. *Economic geography*, *95*(4), 341–361.

Miller, L., Miller, R., & Dismukes, J. (2005). The critical role of information and information technology in future accelerated radical innovation. *Information Knowledge Systems Management*, *5*(2), 63–99.

Molloy, M. & Reed, B. (1995). A critical point for random graphs with a given degree sequence. *Random structures & algorithms*, *6*(2-3), 161–180.

Montresor, S. & Quatraro, F. (2017). Regional branching and Key enabling technologies: Evidence from European patent data. *Economic Geography*, *93*(4), 367–396.

Müller, C. (2002). The evolution of the biotechnology industry in Germany. *Trends in Biotechnology*, *20*(7), 287–290.

Neffke, F. & Henning, M. S. (2008). *Revealed Relatedness: Mapping Industry Space* (tech. rep. No. 18). DRUID Working Paper.

Neffke, F., Henning, M., & Boschma, R. (2011). How do regions diversify over time? Industry relatedness and the development of new growth paths in regions. *Economic Geography*, *87*(3), 237–265.

Nelson, R. R. & Winter, S. G. (1982). *An evolutionary theory of economic change*. Harvard University. Cambridge.

Nesta, L. & Saviotti, P. P. (2006). Firm knowledge and market value in biotechnology. *Industrial and Corporate Change*, *15*(4), 625–652.

N'Ghauran, K. A. & Autant-Bernard, C. (2020). Effects of cluster policies on regional innovation networks: evidence from France. SSRN.

Nishimura, J. & Okamuro, H. (2011). R&D productivity and the organization of cluster policy: an empirical evaluation of the Industrial Cluster Project in Japan. *The Journal of Technology Transfer*, *36*(2), 117–144.

Nooteboom, B. (2000). *Learning and innovation in organizations and economies*. OUP Oxford.

Ochiai, A. (1957). Zoogeographical studies on the soleoid fishes found in Japan and its neighbouring regions. *Bulletin of the Japanese Society for the Science of Fish*, *22*, 522–525.

O'Connor, G. C. (1998). Market learning and radical innovation: a cross case comparison of eight radical innovation projects. *Journal of Product Innovation Management*, *15*(2), 151–166.

O'Connor, G. C. & Ayers, A. D. (2005). Building a radical innovation competency. *Research-Technology Management*, *48*(1), 23–31.

Pandit, D., Joshi, M. P., Gupta, R. K., & Sahay, A. (2017). Disruptive innovation through a dynamic capabilities lens: an exploration of the auto component sector in india. *International Journal of Indian Culture and Business Management*, *14*(1), 109–130.

Pavitt, K. (1985). Patent statistics as indicators of innovative activities: Possibilities and problems. *Scientometrics*, *7*(1-2), 77–99.

Pavitt, K. (1984). Sectoral patterns of technical change: towards a taxonomy and a theory. *Research policy*, *13*(6), 343–373.

Phene, A., Fladmoe-Lindquist, K., & Marsh, L. (2006). Breakthrough innovations in the us biotechnology industry: the effects of technological space and geographic origin. *Strategic management journal*, *27*(4), 369–388.

Porter, M. E. (1998). Clusters and the new economics of competition. *Harvard Business Review*, *76*(6).

Porter, M. E. (2000). Location, competition, and economic development: Local clusters in a global economy. *Economic Development Quarterly*, *14*(1), 15–34.

Porter, M. E. (1990). The competitive advantage of nations. *Harvard Business Review*, *68*(2), 73–93.

Posada, J., Toro, C., Barandiaran, I., Oyarzun, D., Stricker, D., de Amicis, R., … Vallarino, I. (2015). Visual Computing as a Key Enabling Technology for Industrie 4.0 and Industrial Internet. *IEEE Computer Graphics and Applications*, *35*(2), 26–40.

Powell, W. W., Koput, K. W., & Smith-Doerr, L. (1996). Interorganizational collaboration and the locus of innovation: networks of learning in biotechnology. *Administrative science quarterly*, 116–145.

Qi Dong, J., McCarthy, K. J., & Schoenmakers, W. W. (2017). How central is too central? organizing interorganizational collaboration networks for breakthrough innovation. *Journal of Product Innovation Management*, *34*(4), 526–542.

Quatraro, F. (2010). Knowledge coherence, variety and economic growth: Manufacturing evidence from Italian regions. *Research Policy*, *39*(10), 1289–1302.

R Core Team. (2018). *R: a language and environment for statistical computing*. R Foundation for Statistical Computing. Vienna, Austria.

Rhoades, S. A. (1993). The herfindahl-hirschman index. *Federal Reserve Bulletin*, *79*(3), 188–189.

Rivkin, J. W. (2000). Imitation of complex strategies. *Management science*, *46*(6), 824–844.

Robert, E. & Lucas, J. (1988). On the mechanics of economic development. *Journal of monetary economics*, *22*(1), 3–42.

Romer, P. M. (1986). Increasing Returns and Long-Run Growth. *Journal of Political Economy*, *94*(5), 1002–1037.

Rosenberg, N. & Frischtak, C. R. (1983). Long waves and economic growth: A critical appraisal. *American Economic Review*, *73*(2), 146–151.

Rosenberg, N. & Trajtenberg, M. (2004). A general-purpose technology at work: The Corliss steam engine in the late-nineteenth-century United States. *The Journal of Economic History*, *64*(1), 61–99.

Rosenkopf, L. & Nerkar, A. (2001). Beyond local search: boundary-spanning, exploration, and impact in the optical disk industry. *Strategic management journal*, *22*(4), 287–306.

Rothgang, M., Cantner, U., Dehio, J., Engel, D., Fertig, M., Graf, H., ... Töpfer, S. (2017). Cluster policy: insights from the German leading edge cluster competition. *Journal of Open Innovation: Technology, Market, and Complexity*, *3*(1).

Rothgang, M., Lageman, B., & Scholz, A.-M. (2021). Why are there so few hard facts about the impact of cluster policies in Germany? A critical review of evaluation studies. *Review of Evolutionary Political Economy*, *2*, 105–139.

Rowley, T., Behrens, D., & Krackhardt, D. (2000). Redundant governance structures: an analysis of structural and relational embeddedness in the steel and semiconductor industries. *Strategic management journal*, *21*(3), 369–386.

Saviotti, P. P. & Frenken, K. (2008). Export variety and the economic performance of countries. *Journal of Evolutionary Economics*, *18*(2), 201–218.

Scheu, M., Veefkind, V., Verbandt, Y., Galan, E. M., Absalom, R., & Förster, W. (2006). Mapping nanotechnology patents: The EPO approach. *World Patent Information*, *28*(3), 204–211.

Schmoch, U. (2008). Concept of a technology classification for country comparisons. *Final report to the world intellectual property organisation (wipo), WIPO*.

Schoenmakers, W. & Duysters, G. (2010). The technological origins of radical inventions. *Research Policy*, *39*(8), 1051–1059.

Schoenmakers, W., Duysters, G., & Vanhaverbeke, W. (2008). *Radical versus non-radical inventions*. UNU-MERIT.

Schumpeter, J. A. (1939). *Business cycles: a theoretical, historical, and statistical analysis of the capitalist process*. McGraw-Hill New York.

Schumpeter, J. A. (1934). *The Theory of Economic Development*. Harvard University Press.

Scott, A. J. (2006). Entrepreneurship, innovation and industrial development: Geography and the creative field revisited. *Small Business Economics*, *26*(1), 1–24.

Shahin, A., Barati, A., & Geramian, A. (2017). Determining the critical factors of radical innovation using an integrated model of fuzzy analytic hierarchy process-fuzzy Kano with a case study in Mobarakeh steel company. *Engineering Management Journal*, *29*(2), 74–86.

Soete, L. (1987). The impact of technological innovation on international trade patterns: The evidence reconsidered. *Research Policy*, *16*(2), 101–130.

Sonn, J. W. & Storper, M. (2008). The increasing importance of geographical proximity in knowledge production: an analysis of US patent citations, 1975–1997. *Environment and Planning a*, *40*(5), 1020–1039.

Sood, A. & Tellis, G. J. (2005). Technological evolution and radical innovation. *Journal of marketing*, *69*(3), 152–168.

Sorenson, O. & Fleming, L. (2004). Science and the diffusion of knowledge. *Research policy*, *33*(10), 1615–1634.

Squicciarini, M., Dernis, H., & Criscuolo, C. (2013). *Measuring Patent Quality: Indicators of Technological and Economic Value*. OECD Publishing, Paris.

Srivastava, M. K. & Gnyawali, D. R. (2011). When do relational resources matter? leveraging portfolio technological resources for breakthrough innovation. *Academy of Management Journal*, *54*(4), 797–810.

Staehler, T., Dohse, D., & Cooke, P. (2007). *Evaluation der Fördermaßnahmen BioRegio und BioProfile*. BMBF.

Steenhuis, H.-J. & Pretorius, L. (2017). The additive manufacturing innovation: a range of implications. *Journal of Manufacturing Technology Management*.

Sternberg, R., Kiese, M., & Stockinger, D. (2010). Cluster policies in the US and Germany: varieties of capitalism perspective on two high-tech states. *Environment and Planning C: Government and Policy*, *28*(6), 1063–1082.

Stiroh, K. J. (2004). Do community banks benefit from diversification? *Journal of Financial Services Research*, *25*(2-3), 135–160.

Tanner, A. N. (2014). Regional branching reconsidered: emergence of the fuel cell industry in European regions. *Economic Geography*, *90*(4), 403–427.

Teece, D. J., Rumelt, R., Dosi, G., & Winter, S. (1994). Understanding corporate coherence: theory and evidence. *Journal of economic behavior & organization*, *23*(1), 1–30.

Töpfer, S., Cantner, U., & Graf, H. (2019). Structural dynamics of innovation networks in German Leading-Edge Clusters. *Journal of Technology Transfer*, *44*(6), 1816–1839.

Toth, G., Elekes, Z., Whittle, A., Lee, C., & Kogler, D. (2022). Technology network structure conditions the economic resilience of regions. *Economic Geography*, 1–24.

Tripsas, M. (1997). Unraveling the process of creative destruction: complementary assets and incumbent survival in the typesetter industry. *Strategic management journal*, *18*(S1), 119–142.

Tushman, M. L. & Anderson, P. (1986). Technological discontinuities and organizational environments. *Administrative science quarterly*, 439–465.

Uyarra, E. & Ramlogan, R. (2012). The effects of cluster policy on innovation. *Compendium of Evidence on the Effectiveness of Innovation Policy Intervention, Manchester Institute of Innovation Research.*

Uzzi, B., Mukherjee, S., Stringer, M., & Jones, B. (2013). Atypical combinations and scientific impact. *Science*, *342*(6157), 468–472.

Van Beuzekom, B. & Arundel, A. (2009). *Oecd biotechnology statistics 2009.* OECD.

Veefkind, V., Hurtado-Albir, J., Angelucci, S., Karachalios, K., & Thumm, N. (2012). A new EPO classification scheme for climate change mitigation technologies. *World Patent Information*, *34*(2), 106–111.

Verbeek, A., Debackere, K., Luwel, M., Andries, P., Zimmermann, E., & Deleus, F. (2002). Linking science to technology: Using bibliographic references in patents to build linkage schemes. *Scientometrics*, *54*(3), 399–420.

Verona, G. & Ravasi, D. (2003). Unbundling dynamic capabilities: an exploratory study of continuous product innovation. *Industrial and corporate change*, *12*(3), 577–606.

Wanzenböck, I., Scherngell, T., & Fischer, M. M. (2013). How do firm characteristics affect behavioural additionalities of public R&D subsidies? Evidence for the Austrian transport sector. *Technovation*, *33*(2–3), 66–77.

Wassermann, S. & Faust, K. (1994). *Social network analysis: methods and applications.* Cambridge: Cambridge University Press.

Weitzman, M. L. (1998). Recombinant growth. *The Quarterly Journal of Economics*, *113*(2), 331–360.

Whittle, A. & Kogler, D. F. (2019). Related to what? reviewing the literature on technological relatedness: where we are now and where can we go? *Papers in Regional Science*, *99*(1), 97–113.

Wuchty, S., Jones, B. F., & Uzzi, B. (2007). The increasing dominance of teams in production of knowledge. *Science*, *316*(5827), 1036–1039.

Yan, B. & Luo, J. (2017). Measuring Technological Distance for Patent Mapping. *Journal of the Association for Information Science and Technology*, *68*(2), 423–437.

Zander, U. & Kogut, B. (1995). Knowledge and the speed of the transfer and imitation of organizational capabilities: an empirical test. *Organization science*, *6*(1), 76–92.

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