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1 Abstract

In this thesis I start from a combinatorial position where innovations are seen as recombinations of already existing components and define two kinds of recombination. The first is an explorative approach where components are put together in new ways while the other approach, the exploitative one, consists in refining the components themselves. While several studies in the literature have applied similar methods to the construction of technologies, I try to interpret the dichotomy of exploration and exploitation in a relational manner. This relational approach not only extends the understanding of how components are recombined but also challenge the idea of searching for combinations over a highly uncertain, technological landscape. Looking at technologies as combinations of yet other technologies I suggest a more visible landscape made up by the network that emerges when plotting how technologies are related to each other. Measuring influence as the importance of a technology in the continuous technological development, I hypothesize that technologies characterized as either explorative or exploitative will be more influential.

To develop the relational approach to the construction of technology I draw on sociological studies of embeddedness and the benefit of heterogeneity in knowledge creation. Applying concepts from Social Network Analysis I argue for the importance of how technologies are structurally positioned in the larger network of components and why combining distant components can be beneficial. Employing these relational concepts of exploration and exploitation to empirical data consisting of European patents from the hard disk drive industry I show that the relational approach to recombination does help explain why some patents are more influential than others. Finally, I discus the results, look at the restrictions and implications of the study and point to new areas for future research.
2 Introduction

Innovation has long been a buzz word and consultancies specialize in helping companies become better at creating new ideas. However, for many the word innovation remains a fluffy concept. In this thesis I try to approach the subject from an empirical perspective looking at why some new technologies are more influential in the technological development than others. I take my starting point in a definition of innovation as recombination from the economic and management literature and then move on to the empirical research applying said definition on real world data to explain how technologies are constructed. Reinterpreting this definition in a sociological and relational perspective I demonstrate how insights from sociology can be beneficial for the field of technological innovation research while also challenging and extending the discipline of sociology. The definition of innovation serves the dual purpose of restricting and clarifying an understanding of innovation as recombination and as a framework, which I can later reinterpret from a sociological perspective.

Looking through the literature on the construction of technology I find that while the recombinant perspective is often used, it is applied in a highly attributional manner in which technologies are regarded as combinations of technological classification codes. The attributional approach relies heavily on the correctness of the classification system, which can only be developed when components establish themselves as firm categories. Other studies have looked at the interrelationship between technologies viewing other technologies as the components of the focal technology. These studies are, however, often qualitative in nature or restrict themselves to the immediate components. In my view, the consequence of viewing technologies as constructions of other technologies is to incorporate not only an egocentric view of technologies as combinations but to consider the larger structure of the technological network that emerges. My literature review of existing research suggests
that a truly relational approach has not been applied in the field and I therefore turn to a sociological perspective to develop such a strategy, which is the main aim of this thesis.

Drawing on the New Economic Sociology at the focus of embeddedness I reinterpret the concepts of exploration and exploitation in a relational perspective. I then operationalize these concepts using methodology from Social Network Analysis in order to examine how a relational perspective can help explain why some technologies are more influential than others. By influence I mean the impact a certain technology has in future technological development. As I regard technologies as components of yet other technologies, those technologies that are later incorporated as a component in new constructions can be said to have had an influence in the technological development while those technologies that are never reused must be regarded as technological dead ends. In fact I see the level of influence of a technology as the number of times it is used in later combinations and using my relational reinterpretations of exploration and exploitation I state three hypotheses of how a relational understanding of the construction of technology can help explain why some technological combinations are more influential than others. I then test these three hypotheses on empirical data and discuss the contribution of the relational approach in comparison with the existing literature in the field.

By developing sociological perspectives and theories to help explain why some technologies are more influential than others, I try to extend the applicability of sociological methodology to new fields of research. From a more practical viewpoint, the demonstration that a sociological perspective can add explanatory power to existing research in how technologies are constructed is beneficial for companies when searching for new inventions and when examining their product portfolio to see which inventions are worth future investment. Finally, applying sociological theory and methodology to the unrelated field of technology construction I try to demonstrate that the recombinant approach examined in the thesis can
be beneficial in a wider context than just the construction of technology.

3 Aim of Thesis

Using the New Economic Sociology’s focus on embeddedness I try to reinterpret approaches to technology construction in a relational perspective and hereby develop analytical concepts, which are then applied to a large dataset of patents from the hard disk industry.

AIM: The aim of this thesis is to demonstrate how a relational perspective of the construction of technology can add explanatory power of why some technologies are more influential than others.

With this aim in mind I move on to defining innovation as a recombinant search process characterized by exploration or exploitation.

4 Defining Innovation

In this chapter I will give an introduction to the theoretical literature in innovation research from its main contributors in the fields of economics and management science. The main purpose of this review is to provide a good definition of innovation as a recombinant process, which I will later combine with a sociological methodology to develop a novel approach to explain why certain technologies are more influential than others.
4.1 Innovation as Recombination

In the book *Innovation: The Missing Dimension* (2004) Lester and Piore argue that innovative products such as fashion jeans and mobile phones come from integration of earlier distinct production methods and product categories. Thus, Lester and Piore define innovative products as those that create new categories by recombining old ones:

"Without integration across borders separating these different fields, there would have been no new products at all." (2004, p. 15)

There is nothing surprising about the fact that fashion jeans can be seen as the integration of workwear and industrial washing or that a mobile phone consists of different parts such as a screen, some sort of radio signal, a camera etc. but the idea of viewing the larger concept of innovation as a recombinant process is rather radical and stems from the work of the economist Joseph A. Schumpeter. Contrary to other economists and social scientists at that time who thought that the highest technological level had been reached, Schumpeter insisted that it had not since "innovation combines components in a new way, or that it consists in carrying out New Combinations" (Schumpeter, 1939, p. 88).

Thus, instead of viewing innovations as totally new technologies, Schumpeter argued for a conceptualization of innovation in which every innovation builds on already existing technologies and its origins can be traced back to these. This view not only explains how a continuous development is possible but also provides a firm understanding of how new technologies emerge in a recombinant process. Importantly, Schumpeter also notes that certain ideas never leave the drawing board hereby remaining inventions rather than innovations. Thus, an innovation can be either a product or a service as long as it is actually realized and marketed such that an innovation can be defined as a successfully implemented inven-
The idea that innovations have an impact on economic life is central to Schumpeter’s understanding of the economy and the role of innovation. In a later work, Capitalism, Socialism and Democracy Schumpeter reinterpreted Marx’s concept of ‘creative destruction’ by which he understood the sudden decline of incumbents caused by innovations (Schumpeter, 1994[1942]).

The idea that certain innovations are so radical that they can change a market has since been incorporated into the common-sense dichotomy of radical versus incremental innovations with the latter being only minor adjustments to already existing products. Although this pair of concepts provide a valuable framework for analyzing the impact of innovations, in a paper from 1990, Rebecca M. Henderson and Kim B. Clark argue that it is incomplete and extend the framework by making it two-dimensional. Distinguishing between the components of a product and the way they are put together, its architecture, Henderson and Clark explain how what seems to be minor adjustments to products can actually disturb the market and cause the decline of big players just as Schumpeter’s concept of creative destruction (Clark & Henderson, 1990). Thus, innovations can be characterized either by a change in architecture in which new components are put together or by reusing an already existing architecture but refining the components used. This extension of Schumpeter’s framework is useful because it clarifies the idea of viewing innovation as recombination and explains different approaches to the combination of components.

4.2 Innovation as a Search

Schumpeter’s definition and Henderson and Clark’s extension of it is useful because it combines a narrow understanding of the process behind innovation with a broad scope of what can be defined as such. However, while the successful application as a crucial component
in labeling something an innovation seems fair it also makes the definition retrospective in nature. A lot of innovation research has focused on trying to predict such innovations in order to be able to both clarify and provide guidance in what appears to be a highly uncertain search. In a seminal paper from 1991, James G. March proposes to look at how firm invest their resources into either exploiting already existing ideas or exploring new ones (March, 1991). Although focused on organizational learning, the dichotomy of exploitation versus exploration have proved valuable for researchers in the field of technological constructions in which it has been framed as two different methods for searching for innovation (Nerkar, 2003; Rosenkopf & Nerkar, 2001).

While Henderson and Clark focus on the consequence certain innovations have, the use of exploitation versus exploration is aimed at explaining the search process in innovation. Creating a less retrospective framework I thus combine the idea of viewing innovation as a search process characterized by either exploration or exploitation with the recombinant view of innovation. The approaches from Henderson and Clark and March fit well together as innovation involving a change in components can be seen as exploiting an already existing design while a change of architecture is a much more explorative action looking for new recombinations. Innovators in the search for something new can either try to exploit an already proven design by over clocking the components or they can explore new combinations.

The idea of viewing innovation as a search is not new, and several researchers have aimed at explaining why certain technologies are more successful than others in order to provide knowledge to guide future search processes. In a study of innovation from 2001 Lee Fleming and Olav Sorenson draw on work in evolutionary biology to describe how this search can be seen as an optimization process of different combinations (Fleming & Sorenson, 2001; Kauffman, 1993). Employing the metaphor of a technological landscape with maxima and minima Fleming and Sorenson explore how the interdependence among
the combined components change the inventive outcome. I believe that the analogy of a technology landscape describes this search for inventions very well but rather than regarding the landscape as hidden I want to employ a more direct and empirical understanding of a technology landscape in which I regard each technology as embedded among already existing technologies. First, however, I will describe the literature that has dealt with explaining how technologies are constructed from a recombinant perspective.

5 Knowledge from Research on Technology Construction

In this section I first argue for the use of patents as indicators of the construction of technology and afterwards review the findings from the empirical research in the field.

5.1 Patents as Indicators of Technologies

Intellectual property rights of industrial property serve the dual purpose of rewarding people for putting resources into inventing new things while at the same time disclosing this information to enhance further development within the field. The first purpose is fulfilled by granting a patent holder the exclusive right to a patent for up to 20 years in a specific geographical region while the second objective is reached by making the patent open to the public hereby allowing everyone to access and build upon this already established knowledge. For a patent to be granted it needs to fulfill three requirements: 1) the invention must be novel, 2) it must involve an inventive step, and 3) the invention must have potential to be commercialized (EPO, 2012). From these criteria it is clear that patents fit very well into the definition provided in 4 and the work I draw upon all use patents as their data source in examining how technologies are constructed.
It is worth mentioning that patents can only assess the potential for commercialization and not the actual impact this early in a technology’s life. As Schumpeter notes, certain ideas never leave the drawing board hereby remaining inventions rather than innovations. Since patents cannot assess the impact on economic life, studies hereof must be seen as looking at inventive rather than innovative output but with the potential realization as a vital part of being granted and being such an important part of innovation, it seems fair to say that to generate knowledge about these inventive processes is a huge part of explaining innovation. In this sense I regard patents as inventions on the verge of becoming innovations and therefore relevant for innovation research in accordance with other studies (Fleming, 2001; Fleming & Sorenson, 2001, 2004).

When it comes to keeping track of who has the rights to what there is no global institution keeping track of industrial property rights but the Patent Cooperation Treaty includes 130 countries which agree on a set of rules and besides national patent offices the three most important institutions that grant patents are the Japanese Patent Office (JPO), the United States Patent and Trademark Office (USPTO), and the European Patent Office (EPO). A patent can be applied for in a single country or extend into a patent family when filed in different patent offices, which is often the case for highly valuable patents (EPO, 2012). When an inventor sends a patent application to the EPO, for instance, it should include a request for grant, a description of the invention, claims, drawings (if any), and an abstract. As the EPO receives the application it is checked that it meets the aforementioned criteria and then given a filing date.

Meanwhile, a search report is drawn up in which one or more examiners search for documents relevant for assessing whether the patent application meets the criteria for novelty and inventive step. These documents are referred to as backward citations and can be already existing patents or they can be non-patent literature such as scientific papers and
serve the purpose of showing if the patent application is formulated too closely to any of these hereby challenging the inventive step as well as showing the knowledge that the patent application builds upon. The application is then published and later goes through a substantive examination to get granted followed by a validation by the different patent offices involved as well as an opposition period in which third parties can challenge the application. During this process the patent is also classified into technological classes called the International Patent Classification (IPC) codes. These different characteristics describing the patent have been used in trying to understand why some patents are more valuable than others.

6 Empirical Patent Research

In the following I present a literature review of the existing research that applies a recombinant understanding of innovation to patent data in order to explore why some patents are more valuable than others. Going through the different studies, my claim is that there is a development from an attributional towards a more relational understanding of the recombinant perspective. In my opinion, this move is beneficial to develop a more coherent methodology that resembles Schumpeter’s idea of a continuous technological development of new combinations. Rather than viewing patents as isolated constructions retrospectively classified or providing a partly relational methodology I argue for a truly relational approach that views technologies as nested within a broader technological landscape of components.

In a paper from 2001, Lee Fleming develops a methodology to investigate the notion of innovation as recombination using large patent databases and technological definitions from the International Patent Classification (IPC) codes. Conceptualizing the development of new technologies as a search over an uncertain technological landscape, Fleming shows how
new combinations of technologies tend to have more variable outcomes such that they either results in failure or breakthrough (Fleming, 2001). In later papers, Lee Fleming and Olav Sorenson build on this framework of a technological landscape to test other hypotheses of the effect of highly interdependent components and the use of science when searching for new technologies (Fleming & Sorenson, 2001, 2004). Fleming and Sorenson’s findings are very interesting as they only apply a recombinant perspective and the landscape metaphor but their approach is attributional in nature because it only looks at the focal patent and not how technologies are related to each other.

Other scholars have made use of the number and scope of backward citations to earlier patents, hereby employing a different perspective to the concept of recombination (Nerkar, 2003; Rosenkopf & Nerkar, 2001; Podolny & Stuart, 1995). Nerkar (2003) uses backward citations to other patents to explore the temporal dimension in how knowledge is recombined while Stuart and Podolny (1995) go as far as to look at how the earlier patents are interrelated. However, even though these studies all regard earlier patents as building blocks for the new patents citing them they are restricted to the immediate neighborhood of the focal patent. While I described Fleming and Sorenson’s work as attributional, Nerkar and Stuart and Podolny take a first step in a more relational approach by regarding patents as combinations of earlier patents.

Such a relational approach is further extended in later studies. Most of these inquiries (Wartburg, Teichert, & Rost, 2005; Verspagen, 2007; Mina, Ramlogan, Tampubolon, & Metcalfe, 2007) argue for looking outside the immediate neighborhood and analyze the longer linkages of technologies linking to yet other technologies. However, the approach is often qualitative, hereby making it impossible to compare the meaning of these linkages with the existing literature trying to explain patent value, or the focus is on how technological trajectories emerge, not how they can help characterize a focal patent. Only a single study applies
measures developed in Social Network Analysis (SNA) to describe why some patents are more valuable than others but does so from an egocentric approach taking its starting point in the focal patents (Wang, Chiang, & Lin, 2010). While these studies take yet another step towards a relational approach, the lack of quantitative measures make them uncomparable to the existing literature and not analyzing the larger structure of how technologies are related the studies are not truly relational.

I have presented the different studies as common in their approach to the construction of technology as a recombinant process and the use of patents but with differences in how relational approaches they take. Although the studies provide interesting insights, I believe that Schumpeter's understanding of a continuous technological development based on recombinations inherently points to the fact that technologies should not be viewed as isolated inventions. To acknowledge this embeddedness of continuous technological development in a recombinant perspective one must provide a relational approach that can interpret technological development in its context rather than by using artificially created categorizations.

I now turn to sociologically developed theory and methodology to develop new concepts to try and reinterpret the process of innovation in a relational perspective, which I will then apply to empirical data. I see the sociological theory as a starting point for developing a full relational approach to the definition of innovation as recombination, which can continue the movement towards a more relational understanding of the construction of technology.

7 A Relational View of Innovation

The area of innovation is distinctly complex because it involves both developing a good idea and implementing it hereby combining the fields of science and economics. Innovation
research has given attention to different parts of this process from the ideation, the implementation and diffusion as well as the marketing of a product or service but it remains difficult to shed light on the entire process. The sociological perspective on innovation has dealt with the diffusion of technologies (Rogers, 1983[1962]), how to facilitate innovation within and between companies (Burt, 2007[2005]; Stark, 2009), and from a more macro oriented perspective with how to attract innovative workforce (Florida, 2002). In this thesis I aim to provide a sociological approach to the construction of technologies and do so by combining the recombinant view of innovation with the concept of embeddedness in order to develop a set of testable hypotheses.

7.1 The Concept of Embeddedness

Having argued for a position in which technologies can be deconstructed to describe the components that have been combined I now extend the notion of viewing technologies as combinations to regarding them as nested in a larger technological network. Aside from arguing for the relevance of embeddedness, this chapter also serves to introduce a concrete methodology in which I can reinterpret the definitions of innovation as a recombination from a relational perspective.

Since its start, sociology has had the economy as one of its main focus areas. However, while the classic sociologists focused on the dramatic societal changes and their consequences, what has been coined the New Economic Sociology takes it start in changing the critique of economics from the assumption of rationality to that of isolation (Swedberg, 1997). In the article Economic Action and Social Structure: The Problem of Embeddedness, which is regarded the manifesto of the New Economic Sociology, Mark Granovetter put forward the notion of 'embeddedness':
"...the argument that the behavior and institutions to be analyzed are so constrained by ongoing social relations that to construe them as independent is a grievous misunderstanding" (Granovetter, 1985, p. 482)

Granovetter describes how the concept of trust and malfeasance in economic life is indeed dependent upon the personal relations and structures of the situation and hereby argues for a very concrete understanding of embeddedness. One of the first examples of applying this framework was made by Granovetter himself, even before he published the classic article. In his article from 1973, *The Strength of Weak Ties*, Granovetter develops the hypothesis that weak ties are actually extremely influential since they act as bridges for information flows between otherwise distant social groups and hereby enhance individuals’ opportunities and their integration into communities (Granovetter, 1973, p. 1378).

Using Granovetter’s idea of embeddedness I can see technologies as embedded in networks of already existing technologies, which connections can be retraced to learn about the existence of a certain technology and its components. Thus, a technology does not only consist of its direct components as Stuart and Podolny as well as Nerkar posit (Podolny & Stuart, 1995; Nerkar, 2003) since these first order technologies are themselves made up of yet other technologies in the larger network. Thus, applying the concept of embeddedness to the construction of technology, it can be argued that the larger structure of how these technologies are related can provide a valuable source of information in order to explain why some technologies are more valuable than others. While Fleming and Sorenson suggest that the search of innovation is an optimization process over a hidden landscape, I posit that this landscape might be visible as the large network that is made up of technologies building on top of each other.

Most applications of the New Economic Sociology have been seen within network theo-
retical approaches, which have the benefit of being extremely precise in its understanding of embeddedness and heterogeneity (Swedberg, 1997; Granovetter, 2002, p. 54). In the following I introduce the methodology of Social Network Analysis (SNA) and use it to develop a set of hypotheses for how a relational understanding of innovation can help predict the influence of new technologies.

7.2 The Broader Structure of Networks

Although several sociologists have looked at social groups and the difference of ties between people (Simmel, 1902; Durkheim, 1951[1897]; Tönnies, 2002[1887]) the beginning of social network analysis is by and large attributed to the social psychologist Jacob L. Moreno who in the 1930s was the first to systematically record and analyze small networks (Freeman, 2004). In the following decades several anthropologists and sociologists developed similar but different methods but it was not until the 1960s and 1970s where Harrison White and his surrounding students at Harvard University gained interest for the subject that a more coherent methodology came about. This group, among which was Mark Granovetter, introduced concepts from the more mathematically oriented graph theory in order to develop measures used in the descriptions of real networks. Around the same time, also at Harvard University, Stanley Milgram carried out his famous small world experiment in which he sought to prove that real world networks are characterized by short path length between persons and that everyone is no more than ‘six degrees of separation’ away from anyone (Milgram, 1967; Milgram & Travers, 1969).

Milgram’s experiment was realized by sending out a number of letters to a random sample of people in which he asked the person receiving the letter to return it to a specific person in Boston, Massachusetts. However, the person was asked to not send the letter directly to the
target person but to forward the letter to a person they knew, whom they thought would have a better chance of knowing the target person. The second person receiving one of these letters was asked to do the same thing and included with Milgram’s letter was a logbook to record the different persons the letter went through before arriving at its target destination in Boston. By doing so, Milgram sought to find the average shortest path between each person in the USA. Although the results have been widely criticized, the experiment is interesting because it demonstrates not only a general structure in social networks but also the effect of reaching out into a network.

The concept of a shortest path, or a geodesic, is also useful when reinterpreting the exploitative kind in which components are enhanced and applying it to a technological network. If, as argued, technologies can be viewed as recombinations of already existing technologies the large network that forms when a sample of related technologies are mapped will show that some technologies reach far out in the network while others do not have so long traces. The former technologies are those that consist of components, which themselves consist of yet other components and so on while the latter are those that consist of components, which are not just as refined. In other words, if it is possible to map technologies and their components it becomes possible to uncover the technology flows that describe the development of components and their composition. Those technologies which have long traces to earlier technologies can be said to consist of highly refined components while those with shorter traces must be less refined. This leads me to the first hypothesis:

**HYPOTHESIS 1:** TECHNOLOGIES THAT HAVE LONG TRACES TO OLDER TECHNOLOGIES CAN BE SAID TO BE HIGHLY REFINED AND WILL THUS BE MORE INFLUENTIAL THAN LESS REFINED TECHNOLOGIES.
Thus, as Wartburg et al. (2005) notice, to really understand the value of a patent one must assess the antecedent technologies it builds upon. In the framework from Henderson and Clark, and March’s dichotomy of exploration versus exploitation, with this hypothesis I posit that there is value in exploiting already existing designs by refining the components used. While this pretty much covers the exploitative part of refining components I also need to reinterpret the more explorative approach to the construction of technology by looking at how the New Economic Sociology has focused on heterogeneity as something positive.

7.3 Heterogeneity in Networks

In a lot of newer, mostly American, economic sociology there is a positive view of diversity and heterogeneity. Ranging from urban studies of how cities attract the best workforce (Florida, 2002), over productive outcomes in creative industries based on group formations (Uzzi & Spiro, 2005) to studies such as Granovetter’s, there has been a large interest in showing that heterogeneity can be productive although risky. Whilst not directly linked to Schumpeter’s definition of innovation as recombination, the concepts of embeddedness and heterogeneity seem to pair well with viewing innovation as a recombinant process and several sociologists have studied innovation by employing frameworks around these notions.

Most work on innovation and networks have looked at how information flow between people and tried to determine which structural positions are more valuable. In Brokerage and Closure: An Introduction to Social Capital (2007[2005]), Ronald S. Burt rethinks social capital in a concrete, relational perspective and applies his ideas to intra-firm networks. Explaining why some individuals or groups of individuals perform better than others, Burt maps the relations between co-workers and proves that those employees who manage to act as brokers between different relational groups perform better than average. Thus, while the
amount of social ties is definitely important, Burt highlights the fact that the structure of one’s connections is even more important. A person nested within and only having ties to a one clique does not occupy as good a position in the network as the employee who gets information from many different and otherwise non-related cliques. Meanwhile, David Stark goes even further when he argues that innovation is not merely the import of good ideas from the outside but a process in which the best ideas emerge when different groups overlap and dissonance is created (Stark, 2009; Vedres & Stark, 2010).

Applying Burt’s and Stark’s definitions of how combining knowledge from different groups can be beneficial to the technological network I can exchange the groups of people with clusters of technologies, which are tightly knit. Those technologies that combine older technologies from several different technological clusters can be said to be explorative in nature as they combine components, which are not usually combined. Thus, reinterpreting a recombinant view of innovation in a concrete, relational perspective with the new Economic Sociology’s focus on heterogeneity, one would expect that technologies that are made up of elements from distant technological clusters are more innovative than those combining components from the same cluster. This interpretation of explorative innovation leads to my first hypothesis of how a relational understanding of how the explorative approach can provide explanatory power.

**Hypothesis 2:** Technologies that manage to integrate different technological clusters are more influential than those only connecting components within the same cluster.

While this hypothesis covers one part of explorative innovation in a relational perspective, there is also the chance that some technologies combine components within the network
with components outside the network hereby introducing totally new components into the network. This, I believe, is also a sort of explorative combination in the sense that these components have not before been combined to form a technology. In order to account for different types of explorative combinations I therefore posit another hypothesis:

**Hypothesis 3:** Technologies that introduce new components into the network will be more influential than those which do not.

Together, these two hypotheses describe technologies that explore new combinations, either by recombining components already used but in a novel manner or by introducing new components into the technological network. In the following I will turn to describe why patents are a good source for empirically testing the three hypotheses I have stated and then return to an operationalization of my hypotheses.

8 Patents as Networks of Technologies

As I have already argued and can be seen in the literature, patents provide an interesting case of looking at how technologies are constructed and how influential they are. Meanwhile, having developed a more relational understanding of the construction of technology, I must also describe how patents can be used in this scenario. In this section I describe and visualize how I regard backward citations to earlier patents as connections to the components that make up the focal patent.

Generally, backward citations to older patents have been used for assessing how knowledge
flows between inventors, which are the actual humans behind the inventions comparable to the authors of a scientific article (Jaffe, Trajtenberg, & Henderson, 1993). This use has given rise to a discussion of the meaning of backward citations and whether or not they are a noisy indicator of knowledge flows. Backward citations can either be added by the inventors themselves or by the examiner during the search process and the ratio between the two types of citations differ across different patent offices. At the USPTO, it is mandatory that the inventors list all relevant existing patents and failure to do so will result in a rejected application while at the EPO such a list is voluntary. The consequence of this difference is that at the USPTO most backward citations are added by the inventors while at the EPO we see the opposite pattern. (Verspagen & Criscuolo, 2008)

In the field of literature examining knowledge flows, inventor citations are regarded as the better indication that there is in fact a flow of knowledge from one inventor to the other, while citations added by the examiner add noise to the measurement of knowledge flows (Alcácer & Gittelman, 2006; Alcácer, Gittelman, & Sampat, 2009). Because of the differences between the USPTO and the EPO such studies are often made on American patent data although also European research has been done in the field (Verspagen & Criscuolo, 2008). The critique of using patent citations to measure knowledge flows and the noise of examiner added citations is important but in my view also too restrictive. Behind the idea of a knowledge flow lies the assumption that knowledge moves between humans who can then adopt and employ knowledge developed earlier and citations introduced by the examiner thus questions whether the inventors of a focal patent were actually aware of this knowledge or not when applying for a patent.

This ignorance, however, does not exclude that the cited patent is an important part of the focal patent when deconstructing the patent into its parts. On the contrary, the citation system is defined to make sure that new patents cannot claim already invented ideas but
have to show their relations to these (Verspagen & Criscuolo, 2008). In this thesis I am not interested in the flow of knowledge between inventors but merely in the characteristics of the patents and I therefore use backward citations to describe the components that make up the focal technology rather than a flow of knowledge between people (Nerkar, 2003; David, Fernando, & Itziar, 2011). Figure 1 shows how a focal patent with six backward citations is part of a larger network in which its relations to patents outside its immediate neighborhood according to my hypotheses will matter.

![Figure 1: The formation of a technological patent network](image)

As more and more patents are applied for the network grows and it becomes possible to regard this network as a network, or a landscape, of interrelated patents. Such a landscape not only shows which components each patent consists of but also show the position of a patent in the larger structure of the network hereby enabling the possibility of testing my relational hypotheses. There are, however, certain characteristics of this network which are different from other networks and thus worth mentioning.

Most networks are split into either directed or undirected networks depending on whether the relations among nodes can be said to have a direction or not. In 1 I have portrayed the network of patents as directed but in contrast to normal directed networks, ties in the
technological network can not be reciprocated hereby reducing the number of potential ties to half of the number in a normal, directed network (Scott, 2000; Wasserman & Faust, 1994). In this sense the technological network is a hybrid between a directed and an undirected network as ties, or citations, are directed but since patents can not cite each other, there can only be one link between two patents as if it were an undirected network. This distinction will be important in the way I calculate certain relational measures in section 9.

With this landscape metaphor of how patents can be seen as technologies that via backward citations provide information about the components of which they consist and hereby form a large network of interrelated technologies I now turn to operationalize the hypotheses I developed in 7.

9 Relational Concepts for Technology Construction

Having established the idea of patents forming a technological network I now return to my theoretical hypotheses and operationalize them in order to be able to measure them empirically. In the following three subsections I describe how I measure the refinement of components, the integration of technological clusters, and the introduction of new components into the network.

9.1 Refining Components

As argued earlier, the exploitative approach to innovation can be seen as a way of refining components. Earlier patent research has pointed to the fact that familiarity with the components used has a positive effect on the value of the focal patent and highlighted that the
development of technologies can be followed by mapping the connectivity of patents building on top of each other (Fleming, 2001; David et al., 2011). Drawing on Milgram’s experiment of how well connected people in a larger network are, I apply the idea to the technological network of patents and examine to what degree the components used in a focal patent have been refined. Patents that have long traces to earlier patents can be said to consist of highly refined components hereby exploiting and building on top of already existing technological development.

Looking further away than the immediate neighborhood of the focal patent this measure provides a truly relational measure of combinatorial exploitation as shown in figure 2. Here, for each focal patent I extract an outward subgraph made up of all nodes that fall on paths going away from the focal patent hereby forming a tree graph with the focal patent at its root. In each tree graph I then calculate the different shortest paths, or geodesics, from the focal patent and outwards and extract the longest geodesic. For all three examples, the focal patent is placed at the root and enlarged with the longest geodesic colored in red.

![Figure 2: Longest geodesic for three different patents (layout: Reingold Tilford)](image)

A geodesic is a shortest path between two nodes and extracting the longest of these I get a measure of the most refined components of the ones used to construct the focal patent (Wasserman & Faust, 1994, p. 110). As figure 2 shows, there are large differences in how
refined technologies these patents build upon even though they are extracted from the same year. Thus, I regard this measure of refinement as a way to measure exploitative innovation in which components are refined.

9.2 Integrating Technological Clusters

The second hypothesis developed posits that technologies that manage to integrate components from different technological clusters can be said to more explorative and should thus be more influential. In order to define which patents integrate such diverse components I first have to relationally define clusters of technology in the patent network. Modularity is a measure of the structure of networks, which describes the clustering or grouping of a network. Networks with high modularity have many links within groups but sparse connections between them while networks with low modularity seem to more scattered and less clustered. More specifically, modularity is defined as the fraction of the edges that fall within the given groups minus the expected such fraction if edges were distributed at random and lies in the range of [0; 1] (Newman, 2010, 2006, pp. 279). The modularity $Q$ is thus defined as,

$$Q = \frac{1}{2m} \sum_{v,w} \left[ A_{v,w} - \frac{k_v k_w}{2m} \right] \delta(c_v, c_w),$$

where $m$ is the total number of edges in the graph, $A_{v,w}$ is whether there is an edge or not (1,0) between node $v$ and node $w$, $\frac{k_v k_w}{2m}$ is the random expectation of the existence of this edge based on the degrees $k_v, k_w$ of $v$ and $w$, and $\delta(c_v, c_w)$ is the function for whether node $v$ and node $w$ are in the same community (Clauset, Newman, & Moore, 2004). I optimize the modularity measure such that the most links are within clusters and the fewest between.
Iterating over different ways of defining groups in a network, the community structure that yields the highest modularity is then chosen.

Several algorithms have been developed for maximizing the modularity, one of which takes a very simple approach in assigning each node to its own community and then pairing communities according to the largest increase in modularity (Newman, 2004). Despite initially appearing as an enormous task on large networks, only merging communities that have pairs between them drastically simplifies the problem to be calculated in constant time. Afterwards, the division which yields the highest modularity is chosen. In my analysis I employ a mathematically enhanced version of this algorithm presented in Clauset, Newman, and Moore’s paper from 2004 (Clauset et al., 2004) and implemented in igraph for R (Csárdi, 2011) in order to group patents into technological clusters. Figure 3 shows the network of the 3744 patents ordered in 57 clusters by the end of 1983 laid out using the Kamawa Kawai algorithm, which seeks to reduce the amount of crossing edges (Kamada & Kawai, 1989).

While most patents are assigned to only one cluster, some patents seem to also have connections to other technological clusters and I thus count the number of clusters each patent links to when it is introduced into the network. While figure 3 does not show a specific patent which has relations to different clusters, it does give the idea that patents can be grouped according to their relations to form technological clusters, which some patents manage to bridge.

9.3 Introducing New Components

While the first measure of heterogeneity mainly looks at combining knowledge already located within the network, there is also the possibility that a patent introduces components not already present in the network. I therefore propose to use the concept of articulation points
to measure whether a patent bridges two or more otherwise disconnected components of a graph. An articulation point is a node, which, if removed, would split the graph into more components than already present. Figure 4 shows two examples of patents in the same network placed as the root node using the Reingold Tilford algorithm, which gives a good overview of the structure of the network (Reingold & Tilford, 1981). While the first patent shown is not an articulation point because the two patents it links to are already a part of the network, the second patent relates both to patents within and outside the network and thus acts as an articulation point introducing new knowledge into the network.

Together with the concept of bridging different technological clusters, I believe the concept of an articulation point provides a good measure for the explorativeness of a patent. An
explorative technology will be detected either by integrating different technological clusters or by introducing new components into the technological network.

10 Data Construction and Presentation

Focusing on backward citations as indicators of which technological components the focal patent consists of, I prefer backward citations added by the examiner to those added by the inventors. Although there are definitely differences among examiners, the variation is unlikely to be as high as with inventors. As I want to base my analysis on backward citations made by examiners I choose to use data from the EPO rather than the USPTO or the JPO since inventors applying to the EPO are not encouraged to add backward citations themselves and around 90% of all backward citations in the EPO database are made by examiners (Verspagen & Criscuolo, 2008). The OECD has kept a series of datasets describing some of
the variables of each patent applied for at the EPO since 1979 and made them available for research purposes.

The data set consists of patents filed under the IPC-code G11B, which is more commonly known as the hard disk drive industry. While the best approach would be to study the entire network of patents in all fields, computational limitations force me to concentrate on a single field such as that of G11B. The industry of hard disk drives has been studied extensively due to its high pace of innovation and disruptive nature and thus provides an interesting case when examining innovation as recombination (Christensen, 1997). Furthermore, the hard disk as a product seems to fit nicely with the recombinant perspective that I suggest in that a hard disk is a combination of many small parts as shown in figure 5.

![Figure 5: Different components of a hard disk](image)

Besides, there are differences across industries as to how many citations are made to the patent literature. Wanting to extract structural network positions it is crucial that 1) a high share of patents actually cite other patents and 2) that the average citation number is quite high such that different positions actually emerge. While I limit the focal patents to fall within G11B the backward citations of these are not limited in any way and may very well be citations to patents falling outside the focal category. I decide to use all backward citations.
in building the network to get the most complete picture of the technological landscape but in the analysis itself I extract only the focal patents within G11B and compare them among each other.

One of the issues of restricting my sample to the G11B section is that I subtract a part of a larger network at the same time as arguing for the importance of embeddedness. Some patents that link to patents in areas outside G11B might have longer traces, which I cannot assess but at least I capture some of this variation by measuring the articulation point. To solve this issue I could look at the broader network of patents in all IPC sections but this requires a larger computational capacity than I have had access to and also raises problems of differences in citation patterns in different industries. However, while the restriction of the dataset produces some problems I believe they are few and I therefore regard the use of the hard disk drive industry as a good case for testing my relational measures.

Relations among patents are viewed as permanent such that once a patent and its relations are introduced into the network it will stay and relations can only be added to it. The network grows by the number of patents applied for each week from 1979 when the database starts and thus becomes larger and denser each year. Ideally, I would add the patents one by one but due to computational limitations I split the data into months and then add patents to the network each month from 1979 to 2005. Having split the data into months I calculate the different network measures for each group of patents and then combine the 324 months into one large dataset (Wickham, 2011). To restrict the information used to backward citations I only calculate a patent’s network position in the month it is being introduced in the network.

The cumulative network is used for calculating network characteristics while the data set used for analysis consists of the patents applied for between 1985 and 2005. Cutting off the
data set in 2005 is reasoned by the use of a dependent variable which measures the amount of forward citations during the first five years since publication and I thus want to make sure that patents are comparable over this dimension. Meanwhile, I also decide to cut off the first six years of data due to certain network characteristics that could potentially bias the calculation of structural positions. In the article *Six Degrees of "Who Cares?"* Rick Grannis explains how networks tend to exhibit the certain characteristic of a sudden phase transition when moving from several disconnected components into one giant component known from the theory of small worlds (Grannis, 2010). Figure 6 shows the evolution of the network for G11B from 1979 to 2005 year by year with time (years) on the x-axis and the fraction of nodes that make up the giant component out of all nodes in the graph on the y-axis.

![Figure 6: Transition of G11B network as it emerges yearly 1979-2005](image)

The graph clearly shows a transition from one type of network with several disconnected components to a more coherent network in which most nodes are part of the giant component. While it would be straightforward to look at the transition phase as a period in which the
recombinant innovation works at its fullest, the fact that the OECD database was not started until 1979 while the hard disk industry has existed since the 1950's suggests that this transition is a consequence of the database and not an actual development in the industry. Due to the different structure of the network before and after 1985, which is the year when the giant component reaches 70 per cent of the graph, and the consequences it may have for calculating structural positions I therefore cut the data such that I focus on the 21-period between 1985 and 2005.

Finally, I also remove all patents that do not cite any earlier patents since I cannot apply the relational measures developed to these incidents. Although these patents could be described as especially radical and I remove a large part of the sample, these generally have fewer forward citations than the group I keep and by restricting the data I thus remove variation in the dependent variable, which could have shown a false effect of my relational measures. In the next section I will provide information on the dependent variable as well as the key and control variables.

11 Variables Presentation

The data set consists of patents applied for at the EPO between 1985 and 2005 with the main IPC-code G11B. In the following sections I will introduce the variables used.

11.1 Dependent Variable

While patents have been used extensively in innovation literature there remains debate about how to measure their value. In a paper from 2003, Harhoff et. al use a unique dataset
combining a survey on patent value with publicly available patent information in order to assess how to define the value of patents with information available on a larger scale. Comparing informants’ retrospective value assessment of the focal patent with registered data, they find that patent value is correlated with both forward and backward citations, citations to the non-patent literature and especially family size and opposition procedures (Harhoff, Narin, Scherer, & Vopel, 1999; Harhoff, Scherer, & Vopel, 2003). Other studies have looked at the technological importance of patents and found the the number of forward citations is highly correlated with technological importance measured by expert opinions and industry awards (Albert, Avery, Narin, & McAllister, 1991; Hall, Jaffe, & Trajtenberg, 2000; Trajtenberg, 1990). Thus, the number of forward citations can be seen as both an indicator of economic value and of technological importance.

Because of the different opinions on what defines a patent as valuable and the lack of information on family size and opposition procedures in my data set I use forward citations as a measure of influence rather than value. By influence I mean the impact that a focal patent has in the following technological development. The variable *Citations* is thus a count of forward citations received in the first five years after it has been published, which is the period where the number of citations received has peaked (Jaffe et al., 1993; Jaffe & Trajtenberg, 1996). The choice of viewing the number of forward citation as a means of technological importance or influence and the time period of five years is in accordance with already existing literature in the field (Fleming, 2001; Fleming & Sorenson, 2001, 2004; Nerkar, 2003). Forward citations show how many other patents make citations to the focal patent and is thus an indicator of a patent’s influence in the technological development.
11.2 Key Variables

As introduced earlier I have three independent variables of interest. The first one is the count of how many technological clusters each patent links to via its backward citations. The measure, which I call *Heterogeneity*, is made on the basis of a community structure found by optimizing the modularity $Q$ using Clauset et. al’s algorithm and is measured for the focal patents when introduced monthly. I expect this variable, according to the theory, to be positively correlated with the patent value variable, *Citations* but because the complexity of the patent also increases the more clusters are integrated, I use the log-transformed version to account for a curvilinear relationship with decreasing returns to combining categories. The second variable, *Articulation Point*, is a binary measure of whether or not the patent, when introduced, takes a position making it an articulation point between two or more otherwise disconnected components of the graph. I expect to see a positive correlation between the dependent variable and the *Articulation Point*. Finally, I measure the longest geodesic as a measure of *Refinement* and normalize for each month among the patents introduced in the dataset since the possible length of the geodesic changes as the network evolves. In accordance with the concept of exploitation I also expect to see a positive correlation between *Refinement* and *Citations*. (OECD, 2011a)

11.3 Control Variables

In order to control for variables that might influence the relation between my key variables and the dependent variable I consider both relational concepts as well as patent characteristics. In other words I group my controls into relational and attributional controls with the first ones suggested by network studies and the last ones proposed by referenced patent research.
The first relational control variable is that of Degree, which counts the number of relations to other patents and is in effect the amount of backward citations. According to Harhoff et. al, backward citations are positively correlated with patent value and since my relational measures are based on backward citations it is crucial to control for the number of them. Another measure of centrality is the Eigen Vector Centrality, which measures both the focal patent’s relations as well as the relations of those immediate relations hereby enabling a patent to be centrally placed in the network although it has a small degree as long as it is connected to very central patents. As the Eigen Vector Centrality is dependent on the size of the network I scale it to the range [0; 1] when calculated monthly. The last relational control I make use of is the Tree Size of the patent, which for each focal patent counts the number of nodes in a tree graph starting from the focal patent and moving back through all outward backward citations. Also this measure is scaled to the network monthly. I include the Tree Size to get a cleaner measure of Refinement since those patents with large tree graphs have a higher chance of having longer chains by the mere fact that there are more backward connections. (OECD, 2011a)

Besides these relational measures developed in network analysis I include a number of attributional control variables. First, the variable Self Citation is binary and measures whether the focal patent in its citations cite at least one patent which has been applied for by the same company. With this variable I try to account for the fact that companies building on already existing knowledge by developing similar patents might produce better patents. Second, as Harhoff et. al show a correlation between citations to the non-patent literature and patent value, I include the variable NPL Citations, which is a count of citations to non-patent literature, often signifying a patent building on scientifically developed knowledge. In accordance with Fleming and Sorenson I also include the number of technological classes IPC Codes, which is known for signifying the degree of complexity in the patent as well as the
number of technological categories *IPC Sections* to account for the broadness of the patent (Fleming & Sorenson, 2001). While these two measures can be said to be non-relational aspects of the recombination I am looking for I simply include them as a last test.

The last two variables directly related to the patents are *Granted* and *Withdrawal*, which are binary variables for whether a patent has been granted or withdrawn. While excluding non-granted patents would seem to provide a more leveled ground for comparison, patents can have both forward and backward citations although they have not been granted and besides removing variation in the dependent variable I also risk to create a biased network if I remove them from the sample. Instead, I decide to include a dummy as to whether the patent was granted or not while keeping patents that were not granted in the sample. Likewise with *Withdrawal*, which defines whether a patent was withdrawn or not. Patents can be withdrawn throughout the granting procedure and after if there is no longer a reason for the company to keep paying for its rights. Therefore, excluding those patents that are withdrawn would create a bias since patents from the earlier periods would have a larger chance of being withdrawn and I therefore include a dummy to account for this variation while keeping all patents in the sample. (OECD, 2011a)

Introduced by Harhoff et. al, another measure that describes the value of a patent is the family size, which is essentially the number of countries in which the patent is applied for. While I do not have the family size for each patent I do have an indicator as to whether the patent was also applied for at the USPTO and the JPO, which as mentioned, are the other two large patent offices (OECD, 2011d). As patents that are applied for in the three large offices must be expected to have a larger potential, I include a dummy variable, *Triadic*, to take up some of the variation from family size. Finally, I also include a count variable for the number of *Inventors*, which can be assumed to be a proxy for investment in the patent (OECD, 2011c). In the following section I provide descriptive statistics and a correlation
matrix for the variables used.

12 Descriptive Statistics

In this section I lay out descriptive statistics for the variables just presented. Table 1 shows the mean, standard deviation, minimum and maximum for dependent, key, and control variables including all 19183 observations.

Table 1: Descriptive Statistics

<table>
<thead>
<tr>
<th></th>
<th>Mean</th>
<th>Std. Deviation</th>
<th>Minimum</th>
<th>Maximum</th>
</tr>
</thead>
<tbody>
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<td>-1</td>
<td>13</td>
</tr>
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<td>1.000</td>
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Next, a correlation matrix in table 2 shows how the different variables are related to each other. Of most importance here is to note that all but two variables are significantly correlated with the dependent variable. The two variables are *E.V. Centrality* and *IPC Sections*. In other words none of these variables seem to be able to explain the variation in *Citations* but I still keep them in the final equation since the two are key controls in network and patent research respectively. Apart from this oddity, I notice that *Articulation Point*
is negatively correlated with \textit{Refinement} while \textit{Heterogeneity} is positively correlated with \textit{Refinement}. I would have expected that the two variables measuring exploration would have similar relationships with the variable measuring exploitation and probably a negative one since technologies would either be highly refined or very explorative. In this case it seems that some technologies are both highly refined and integrate different clusters of technology, which is probably because patents that have large tree graphs are also those that bridge different clusters. I therefore expect this to be something I can control for when introducing \textit{Degree} and \textit{Tree Size}. 
Table 2: Correlation Matrix

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<td>0.01</td>
<td>-0.08</td>
<td>-0.04</td>
<td>-0.00</td>
<td>-0.05</td>
<td>0.05</td>
<td>0.03</td>
<td>0.09</td>
<td>-0.02</td>
<td>-0.03</td>
<td>0.00</td>
<td>0.39</td>
</tr>
</tbody>
</table>

* p < 0.05, ** p < 0.01, *** p < 0.001
With these correlations in mind I now turn to the model specification.

13 Model

As I try to model a count variable I consider both the poisson and the negative binomial distribution. The poisson distribution is the most basic form for modeling a count variable but is also quite restrictive because it, as shown, in equation (1) only has one parameter, \( \mu \), the rate of change. This forces the mean and the variance of the dependent variable to be equal, which as we saw in table 1 is not the case (Cameron & Trivedi, 2005; Wawro, 2010, pp. 666).

\[
Pr[Y = y] = \frac{e^{-\mu} \ast \mu^y}{y!} \tag{1}
\]

Instead, the distribution of Citations is over dispersed because the variance is larger than the mean hereby breaking the assumption of equidispersion (see table 1). Besides, in a poisson regression it is also assumed that there is independence of events such that the forward citations of a focal patent are not in any way related. This is also questionable as we can imagine the likelihood of receiving a citation increases having received the first one because examiners might have tendencies to cite popular patents or patents they already know. This instead leads me to consider the negative binomial distribution, which has another parameter to adjust and is thus more flexible than the poisson regression as shown in equation (2).
\[ P[Y = y] = \binom{r + y - 1}{y} p^r (1 - p)^y \]

(2)

In order to test if my assumption of preferring the negative binomial distribution over the poisson distribution is correct I plot the observed frequencies of the dependent variable, \textit{Citations}, against the negative binomial and poisson distributions calculated using moments from the actual data. In figure 7 I show the actual distribution of the dependent variable with a poisson and a negative binomial distribution respectively fitted to the data. (Cameron & Trivedi, 2005)

Figure 7: Poisson and Negative Binomial distributions fitted to data
As the figure shows, using the mean of the observed frequencies the poisson distribution provides a limited fit while the negative binomial distribution seems to better adjust to the skewness of the actual data which is both over dispersed and has an excess of zeros. It should be mentioned that the distribution of the dependent variable changes over the years from 1985 to 2005 challenging the predictive power of the model in the later years. None the less I decide to use a negative binomial regression to better fit the over dispersion of my dependent variable. This choice of model is in accordance with earlier work on patents (Fleming, 2001; Fleming & Sorenson, 2001, 2004; Nerkar, 2003).

Another issue, where I decide to follow existing guidelines despite knowing that it is problematic is related to combining social network analysis and regression techniques. In most regression models, including the negative binomial, there is an assumption of independent and identically distributed observations. Using the case of the HDD industry and employing social network measures on the data it is obvious that the observations are not independent of each other. This can potentially violate the assumption of independent and identically distributed observations, which may not bias the coefficients but could lead to inflated standard errors (Wawro, 2010, pp. 138). Although this is an issue with most network studies, it has yet to be solved and in this thesis I follow existing literature in the field by employing regression techniques on network data despite the potential problems (Vedres & Stark, 2010; Burt, 2007[2005]).

The issue is also relevant in patent research where it is clear that observations, if taken from a specific industry and not sampled from the larger database, must also be related in some way. However, the existing literature on patent research does not deal with the fact that patents are in fact related in their sampling techniques (Fleming, 2001; Fleming & Sorenson, 2001, 2004; Nerkar, 2003). Again, I follow precedence within the literature by employing the same techniques and furthermore I will argue that employing a relational approach to
the field of patents as a second benefit I also point to the methodological issue that the demonstrated interrelatedness of patents might have. The model I estimate incorporates all three key variables as well as relational and attributional controls as shown in equation (3).

\[ Citations = \beta_1 \ast \log(Het) + \beta_2 \ast Art + \beta_3 \ast Ref + \beta_4 \ast R + \beta_5 \ast A + \text{constant}, \quad (3) \]

where \( Citations \) is the count of forward citations received within the first five years, \( Het \) is the count of how many technological clusters a patent links to, of which I take the logarithm as I expect there to be a decreasing return to increasing the complexity, \( Art \) is whether or not the patent introduces new knowledge into the network, and \( Ref \) is the longest geodesic, normalized monthly. Aside from the dependent variable and my key variables I split the controls into relational controls, \( R \), and attributional controls, \( A \), as well as a constant. When presenting my results I start out with a simpler model to show how my key variables act once I start adding controls but this is the full model, which I end up with. Besides the different control variables I also try to reduce the endogenous variation coming from the companies applying for patents.

13.1 Fixed Effects

As with inventors, there is very little information on the companies that apply for patents in the database I use and since I expect that a lot of variation in the dependent variable can be explained by company characteristics, which I do not have, I include company fixed effects. By restricting the patents to those applied for by companies with 25 or more patents during the period from 1985 to 2005 I can run a regression including a dummy for each company to account for most of the variation coming from this source (OECD, 2011b). This leaves me
with 75 companies holding a total of 13071 patents between 1985 and 2005.

Furthermore, I also include year dummies to account for the fact that there are differences in how many citations patents have received through the period. Using 1985 as a reference year I include a dummy for each of the years 1986-2004. In the following, I present results from different models, which are all calculated using robust standard errors to account for the heteroscedasticity intrinsically linked with a count variable (White, 1980; Cameron & Trivedi, 2005).

14 Results

In this section I present the results from estimating the model suggested in section 13 and describe the robustness check I make to validate the results.

14.1 Negative Binomial Regressions

Table 3 presents five different models from the most basic with only my key variables to the full model with all controls, relational as well as attributional. All models, however include year dummies and company fixed effects. Model 1 shows highly and significant estimates for all three key variables, which are, as expected, positive such that both the exploitative and explorative uses of components are positively correlated with patent influence. In the second model, where I include only the relational control variables, we see a slight decrease in all parameter estimates, which are, however, still positive and significant. Most notable is the decline of the parameter of Refinement, which is halved due to the introduction of Tree Size. In model 3 I include only the key variables as well as the amount of attributional controls
not concerning the scope and complexity of the patent. As expected, when comparing the parameter estimates of model 3 to model 1, the attributional controls do not remove any of the variation explained by the key variables.
<table>
<thead>
<tr>
<th></th>
<th>Model 1</th>
<th>Model 2</th>
<th>Model 3</th>
<th>Model 4</th>
<th>Model 5</th>
</tr>
</thead>
<tbody>
<tr>
<td>Heterogeneity, log.</td>
<td>0.189*** (0.044)</td>
<td>0.155*** (0.046)</td>
<td>0.199*** (0.043)</td>
<td>0.177*** (0.045)</td>
<td>0.123** (0.044)</td>
</tr>
<tr>
<td>Art. Point</td>
<td>0.120*** (0.034)</td>
<td>0.097** (0.036)</td>
<td>0.130*** (0.033)</td>
<td>0.115** (0.035)</td>
<td>0.108** (0.035)</td>
</tr>
<tr>
<td>Refinement, norm.</td>
<td>0.158*** (0.018)</td>
<td>0.070** (0.026)</td>
<td>0.167*** (0.018)</td>
<td>0.084*** (0.025)</td>
<td>0.092*** (0.024)</td>
</tr>
<tr>
<td>Tree Size, norm.</td>
<td>0.091*** (0.021)</td>
<td></td>
<td>0.087*** (0.020)</td>
<td>0.050** (0.019)</td>
<td></td>
</tr>
<tr>
<td>E.V. Centrality, norm.</td>
<td>0.004 (0.011)</td>
<td></td>
<td>0.005 (0.010)</td>
<td>0.008 (0.010)</td>
<td></td>
</tr>
<tr>
<td>Degree</td>
<td>0.017** (0.006)</td>
<td></td>
<td>0.012* (0.006)</td>
<td>0.011 (0.006)</td>
<td></td>
</tr>
<tr>
<td>Inventors</td>
<td></td>
<td>0.052*** (0.008)</td>
<td>0.050*** (0.008)</td>
<td>0.041*** (0.008)</td>
<td></td>
</tr>
<tr>
<td>Self Citation</td>
<td>-0.025 (0.030)</td>
<td>-0.037 (0.030)</td>
<td>-0.019 (0.030)</td>
<td></td>
<td></td>
</tr>
<tr>
<td>NPL Citations</td>
<td>0.113*** (0.015)</td>
<td>0.114*** (0.015)</td>
<td>0.087*** (0.015)</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Granted</td>
<td>-0.015 (0.057)</td>
<td>-0.017 (0.057)</td>
<td>0.016 (0.057)</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Withdrawal</td>
<td>-0.251*** (0.059)</td>
<td>-0.247*** (0.059)</td>
<td>-0.204*** (0.058)</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Triadic</td>
<td>0.222*** (0.046)</td>
<td>0.217*** (0.046)</td>
<td>0.186*** (0.044)</td>
<td></td>
<td></td>
</tr>
<tr>
<td>IPC Codes</td>
<td></td>
<td>0.074*** (0.005)</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>IPC Sections</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td>-0.115*** (0.030)</td>
</tr>
<tr>
<td>Constant</td>
<td>0.129 (0.346)</td>
<td>0.083 (0.345)</td>
<td>-0.285 (0.305)</td>
<td>-0.303 (0.304)</td>
<td>-0.282 (0.292)</td>
</tr>
</tbody>
</table>

Year Dummies: Yes, Fixed Effects Companies: Yes

Robust standard errors in parentheses

* p < 0.05, ** p < 0.01, *** p < 0.001
Then, in model 4 I include both relational and attributional controls and although parameter estimates are still lower than in model 1, they are all significantly positive. Finally, in model 5 I include *IPC Codes* and *IPC Sections*, which can be said to describe the complexity and scope of the patent hereby interfering with the same characteristics as my exploration measures. While *Articulation Point* diminishes only a little and *Refinement* even grows, the *Heterogeneity* variable declines to a considerably lower level. It seems, thus, that these extra two controls, as expected, are related to the key variables concerning exploration while not affecting the exploitation key variable. However, the fact that the key variables remain positive and significant even with the introduction of these attributional versions suggests that a relational aspect offers increased explanatory power when explaining why some patents are influential than others.

As the negative binomial regression is not linear the predicted change of the dependent variable given a change in one of the regressors is dependent on the base of the regressor. However, since the model is estimated using the log of the dependent variable *Citations*, I can calculate the incidence rate ratio (IRR) by taking the exponent of the estimated coefficients, which can then be interpreted as the percentage change in $y$ for a one unit change in $x$. In the following I present IRRs for the significant variables in Model 5 in table 3. Starting with *Heterogeneity*, which is itself log-transformed, has an IRR of 1.13, meaning that for a 1% change in $x$, $y$ changes changes with 1.131% percent holding everything else constant. Meanwhile, *Articulation Point* has an IRR of 1.114 such that, ceteris paribus, technologies that introduce new components into the network receive 11.4% more *Citations* than those combining technologies already in the network. Finally, the IRR of *Refinement* is 1.096 meaning that a one unit increase in $x$, which is in effect an increase of one standard deviation due to the normalization, is associated with a 9.6% increase in $y$ holding everything else equal.
Although these coefficients do not sound of much, comparing them to some of the well known indicators of patent influence it is fair to say that the relational perspective does add explanatory power. While Articulation Point was associated with a 11.4% increase in $y$, patents characterized as Triadic on average have 20.4% more Citations than those only applied to one or two of the three large patent offices. Comparing the other two key variables to indicators, which the literature has found significant, we see that ceteris paribus a one unit increase in NPL Citations is related to a 9.1% change in $y$, adding another inventor leads to a 4.2% increase in Citations, and a one unit change in the number of IPC Codes is associated with a 7.7% increase in $y$. Aside from IPC Codes, which is both the most significant and the most important parameter given its large range, the relational key variables are important when trying to predict the future influence of a patent based on the information given in the search report.

14.2 Robustness Check

As a means of testing if my results are valid in different scenarios I do a robustness check relating to the reduction in sample size by restricting the sample to patents held by companies with 25 or more patents. As a robustness check I run a regression on all 19183 observations and instead of the company fixed effects I include a control for the number of patents each company holds when applying for the focal patent. I call it a measure of Experience because it computes the experience each company has within the HDD industry when applying for the focal patent and thus takes away some of the variation coming from the companies. The robustness check shows similar results to the model presented and can be seen in the appendix.
15 Discussion

In this section I will discuss the results from the main model in table 3. I will split the main discussion into two parts concerning the three hypotheses of my relational understanding of exploration and exploitation but also touch on interesting results of the control variables.

15.1 Hypothesis of Exploitative Combination

Starting with hypothesis, which stated that more refined technologies would be more influential, this also proved to be the most robust. In both the main model and the robustness check, the *Refinement* variable proved to have a highly significant effect on the number of *Citations*. Besides, the incidence rate ratios showed that *Refinement* was as important as *NPL Citations* and *Inventors*, which are normally known for being very important predictors of the influence of a patent. Although not as important as the number of *IPC Codes*, I conclude that the relational interpretation of exploitation is valuable when trying to explain why some patents become more influential than others. This is not surprising given the already existing and predominantly qualitative literature on how technological trajectories develop and although these studies focus on predicting the trajectories themselves rather than the influence of patents, there are certain ideas for improvement to be found in the literature.

Especially the more quantitative studies of technological trajectories have interesting ways of looking at the connections created by citations. When backward citations are seen as links to the components combined, it is obvious that a patent only linking to one older patent can be seen as a direct successor while a patent with three backward citations is derived from all three older patents. Using weighted edges it can be argued that the strength of linkage between two patents shall be computed as the inverse of how many patents a focal
patent builds upon such that the weight of an edge between a patent and its sole backward citation is one whereas the weights of three edges from a focal patent to three antecedent patents must be $\frac{1}{3}$ each. In my relational interpretation of exploitative search for innovation, I employed the quite simple measure of a geodesic measured in an unweighted and directed network and did control for the number of nodes in the ancestral tree graph of each patent but to gain more information from technological trajectories, weighing edges is an interesting approach. (Wartburg et al., 2005; Choi & Park, 2009)

15.2 Hypotheses of Explorative Combination

Moving on to the two hypotheses of exploration I posited that patents that either combine components from different technological clusters or introduce new components into the network would be more influential in the following technological development. I believe that both hypotheses were validated although not as convincingly as the one on exploitation. The results from the first hypothesis, measured with the Heterogeneity variable, showed that there was a decreasing return to integrating more and more technological clusters. This suggests that the scope of the invention or the challenge of combining such diverse components can be too complex and is in accordance with the literature (Fleming & Sorenson, 2001). Perhaps this finding is due to the fact that very radical inventions that combine many different components might also be very far from the market and need to be more refined in order to have a larger impact on the technological development.

Looking at the existing literature related to this hypothesis, several studies have found evidence for related although different forms of exploration. As referenced earlier, Nerkar (2003) finds a curvilinear relationship between temporal exploration and impact while discovering a linear relationship between temporal exploitation and impact. Although providing
similar results, Nerkar’s research is based on a temporal dimension of search whereas I base
mine on the spatial dimensions of the network of patents. Another study, which is closer to
the spatial dimension is Schilling and Green (2011). Although using articles from the social
sciences as their data source, Schilling and Green also employ a recombinant perspective
and demonstrate that articles having atypical connections to otherwise non-related fields are
positively correlated with high-impact articles (Schilling & Green, 2011). It seems, thus,
that there are several findings in the literature of recombinant innovation studies that find
more robust effects of the explorative approach to innovation and I believe that part of the
lack of robustness in my results is misspecification.

More specifically, there are two places where I think a superior methodology could im-
prove the *Heterogeneity* variable to better capture how some technologies combine hitherto
non-related components. The first is the use of the modularity measure on a patent network,
the second is the optimization of it. The modularity measure was developed for undirected
and unweighted networks and is only recently being ported to directed and weighted net-
works. As just mentioned, there is a possibility that I could get more information from
analyzing the patent network using edge weights proportionately with the number of edges
between patents. Besides, the patent network is a hybrid between a directed and an undi-
trected network as citations are definitely directed but without the possibility of reciprocity,
the characteristics of the patent network more resemble those of an undirected network. De-
liberately, I decided to apply the modularity measure on an undirected edition of the network
and then transfer the findings to the directed network. Either employing another concept
for detecting communities or using a newer form of modularity developed for directed and
weighted networks could potentially lead to better results. The second issue is related to the
optimization process, where I, due to computational limitations used the fast greedy algo-

rithm. This algorithm has later been replaced by more precise and just as fast algorithms

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but they are jet to be implemented in the most common statistical software packages.

As the other side of testing explorative combinations I posited the variable *Articulation Point* to account for those patents introducing new components into the network. As with *Heterogeneity* the dummy variable proved to have a positive significant relationship with the influence of the patent but also a modest one. One of the issues with this variable is the fact that 75.2% of the patents actually occupy an articulation point (see table 1), which in my view are too many to classify as distinctly explorative. Besides, because I only use the giant component of the entire network of G11B the variable quickly becomes a control variable for those patents having relations outside the giant component rather than a true measure of exploration. Although it is without doubt that patents lying at articulation points do introduce new components into the network, I know very little about these new components and they could, among other things, hide long technological trajectories. Therefore, I find it difficult to make too bold conclusions based on the results for this variable besides noting that it would definitely be beneficial to extend the analysis to a larger part of the patent network.

15.3 Other Considerations

Other interesting findings from section ?? include the lack of significance of *E.V. Centrality*, *Granted*, and *Self Citation* as well as the negative sign of *IPC Sections*.

The fact that *E.V. Centrality* is insignificant I interpret as an indication of how different patent networks really are. If correctly specified I believe the insignificance points to the problem of using concepts from social network analysis to the hybrid network of patents. My use of both ego- and sociocentric relational measures of exploitation and exploration have been developed in accordance with innovation literature and applying already existing
measures from social network analysis would not have been sufficient to understand the patent network. I conclude that the measures I have developed, and which take their start in social network analysis, have proved to significantly improve the explanatory power of why some patents are more influential and also pointed to the fact that patent networks are inherently different and thus need a specific methodology compared to the study of social networks.

Meanwhile, also the dummy variables *Granted* and *Self Citation* are both insignificant, which is quite surprising. I had expected a positive correlation between the dependent variable and whether or not the focal patent has been granted but the insignificant coefficient could be due to very radical patents not being granted because they are too far from commercialization although having a large impact. The insignificant parameter of *Self Citation* is in opposition to the literature referenced but it is worth remembering that I use the EPO database in which backward citations are primarily introduced by examiners and not inventors themselves as when applying for the USPTO. Some patents are applied for at different offices and will then include the search report from the office where it was first published. This is the case for patents applied to at USPTO but since I control for these patents with the *Triadic* variable this should not be an issue. However, although I make use of the EPO database and control for those patents including search reports from the USPTO I still think there should be a positive correlation, just due to the fact that companies specialize in certain areas rather than entering all markets and the real explanation of the insignificant parameter might be found in the fact that I study the limited industry of hard disk drives.

The last issue I wish to touch upon is the significant and negative coefficient of *IPC Sections*. In a recombinant perspective this can be seen as an attributional measure of explorative innovation and we would thus expect a positive sign. Besides, with the broader the scope of a patent one would expect it to receive more forward citations, simply because it
should have a larger probability of being cited by appearing in more sections when examiners search for prior art. I thus interpret this negative parameter estimate as an argument against the latter explanation, namely that broader patents are not necessarily cited more often while patents that are not only characterized by broadness but which actually combine components in new ways, according to my measures of exploration, are more influential.

16 Conclusion

In the following I draw up a summary of the findings, then discuss the restrictions of the study and finally touch on implications and further perspectives.

16.1 Summary

The aim of this thesis was to examine whether a relational approach developed from sociological theory and methodology could add explanatory power in clarifying why some technologies are more influential than others. This question was justified looking through existing patent research, which I argued, had a highly attributional or egocentric approach to technology construction rather than a truly relational approach. In order to answer this question I first defined the process of innovation as a search for combining already existing components in novel ways, either by exploiting already existing designs and enhancing the components or by exploring new combinations of components not otherwise related.

Using the concept of embeddedness an methodological concepts from Social Network Analysis, I then reinterpreted the notions of exploitative and explorative innovations in a relational perspective and applied it to the empirical case of European patents in the hard
disk industry from 1985 to 2005. Controlling for attributional variables proven important in explaining a patent’s influence and variables suggested by the general studies of networks, I found significant and positive correlations of my relational concepts for both exploration and exploitation. Validating my results with different robustness checks I have made plausible the importance of embeddedness in the construction of technology. In the following I touch on the restrictions I see in the analysis.

16.2 Restrictions

When looking at the restrictions of this study, three things seem obvious: the lack of a causal statement, the problem of interrelatedness, and the small scope that a study of a specific industry in a specific continent will always have. In the following I discuss these three issues starting with the problem of causality.

Causality has always been a problem in studies of social networks and there is no exemption in this study (Doreian, 2001). While it seems straightforward that relations in the larger structure of a social setting are important it is more difficult to isolate their effect because of endogeneity problems and the lack of exogenous events that change relations in a known way. Although there is a clear temporal difference between the backward citations on which the key variables are based and the dependent variable of forward citations, we explain so little of the variation in the dependent variable that there could easily be an omitted variable bias (Wooldridge, 2003, pp. 93). Correlations are, however, still of interest and in accordance with literature in the field I see the findings as non-causal relationships.

Another issue, which is critical to network studies, is the problem of interrelatedness among observations, which can potentially then lead to autocorrelated residuals (Wawro, 2010, pp. 138). Knowing quite well that my model have these traits I follow precedence
within the field of patent research when estimating and interpreting my model in order to secure comparison with earlier studies. Besides, there seems to be a problem in the fact that the backward citations of one patent can be the forward citations of another, earlier patent. The latter issue stems from the fact that I focus on a specific industry over years and could be removed by looking at the larger network of patents in all industries in a cross-sectional analysis but I have experienced computational limitations in such an approach. This also highlights the issue of restricting my focus to a specific industry and patent office, hereby reducing the generalizability of the study. While there are computational limitations to the first issue, the second issue arise because there is not one single institution keeping track of patents and because the different patent offices have different characteristics suitable for different kind of analyses.

Although limited by these three restrictions, in the following I try to touch on some of the implications and perspectives my findings bring about and also discuss future research.

16.3 Implications and Perspectives

In this final section I discuss the different implications I believe my findings have for the literature of patent research and sociology and also look for elaborations and future research.

In this thesis I have focused on explaining why some patents are more influential than others and therefore restricted my data basis to backward citations. It could be interesting, however, to apply a similarly relational perspective to forward citations to see how far and broad certain patents manage to become influential. In other words, rather than measuring impact on the mere count of citations, one could assess the structure of those citations in different steps. This could help identify those patents that act as multipurpose technologies which are used in many different areas but would also serve as an elaboration of sociological
diffusion studies looking at how technologies diffuse to and are used in different areas from where they originated.

There are a few implications of this study for the literature of patent value and the construction of technology. Applying the relational concepts of exploitation and exploration to empirical data I showed how a sociologically developed methodology can help explain why some patents are more influential than others. Doing so I not only reinforced already existing literature pointing to the value of multistage patent analysis (David et al., 2011; Wartburg et al., 2005) but also suggested the larger structure of the patent network to be of importance. Reinterpreting the combinatorial perspective introduced by Schumpeter and applied to patents by Nerkar and Fleming and Sorenson (Nerkar, 2003; Fleming & Sorenson, 2001, 2004) I have suggested a new approach for looking at innovation as new combinations of already existing components. These suggestions include the idea of using the landscape metaphor in a more direct and visible way to explain how certain inventions perform better than others. While these implications regard the field of patent research and technology construction as well as the companies when analyzing the value of their patents, I believe my findings also has significance for sociology.

With the New Economic Sociology and following work, sociologists have taken a turn to a more relational approach in which connections and social structure have seen increasing focus. My findings suggest that sociological ideas and methods can be successfully applied to related fields, which have otherwise received less attention from sociologists. A stream of literature within sociology that takes the relational approach even further is that of Actor-Network Theory (ANT) in which the word social is defined by the presence of relations rather than the material of the actors studied (Latour, 2005). ANT studies are based on the belief that the distinction between culture and nature is false and therefore give equal
attention to human as well as non-human actors. The field of patent research lends itself well to an approach in which inventors, companies, IPC codes, and earlier patents can be seen as one large, technological, multimode network. In my analysis I tried to account for relations to many of these human and non-human actors but in an attributional manner where I restricted the relational perspective to earlier patents. A real ANT approach would extend the relational approach to all those actors and ideas and using a methodology similar to what I have applied could also provide an interesting and more quantitative methodology of ANT, which apart from a few more recent studies, has been a predominantly qualitative field (Latour, 2010, 2012).

On a final note I thus see several implications for patent research and the construction of technology as well as emerging fields for bringing together the different perspectives of sociology with new areas of research.
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Appendix

Robustness Check

In this section I provide the estimations from the robustness check where I include all companies and instead of using fixed effects I introduce a variable, Experience, which counts the number of patents each company holds and adds it as a characteristic of each patent to tell whether the patent is applied for by a highly experienced competitor or not.
Table 4: Robustness Check

<table>
<thead>
<tr>
<th></th>
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<td>0.127**</td>
</tr>
<tr>
<td>Art. Point</td>
<td>0.126***</td>
<td>0.112***</td>
<td>0.163***</td>
<td>0.144***</td>
<td>0.155***</td>
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<tr>
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Robust standard errors in parentheses
* p < 0.05, ** p < 0.01, *** p < 0.001