Innovation und Entrepreneurship

Hrsg.: Nikolaus Franke, Dietmar Harhoff und Joachim Henkel

Philipp Sandner

The Valuation of Intangible Assets

An Exploration of Patent and Trademark Portfolios

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Innovation und Entrepreneurship

Herausgegeben von
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Foreword

Companies need intangible assets such as knowledge and brands to develop and to sell new products. Although intangibles become increasingly important, formal reporting procedures to reliably assess their monetary value do not exist. In his dissertation, Philipp Sandner aims at examining portfolios of intellectual property (IP) rights to assess the market valuation of companies' intangible assets. Specifically, patents and trademarks are used to approach technology-based and market-based assets, respectively. He applies econometric methods to a unique dataset which he assembled specifically for the purpose of this thesis.

The thesis consists of four main chapters. First, Philipp Sandner presents in some detail the European trademark system. Research in business administration and economics has rarely relied on trademark data, and the complexity of the institutions is presumably one reason for the current dearth of studies. The first chapter in this study creates a sound foundation for the subsequent chapters. It is also helpful to other researchers who wish to understand the trademark system. The next chapter analyzes the contribution of R&D, patents and trademarks to companies' market value. Philipp Sandner is one of the first authors to quantify the impact of different types of intangibles. In another chapter he scrutinizes trademark portfolios in-depth and explores different filing strategies employed by companies. In the final chapter, he analyzes patterns of stock movement and traces them back to the effect of technology- and market-based assets.

The thesis presented by Philipp Sandner delivers new research insights which deepen our understanding of how technology- and market-related assets contribute to the market value of firms. This book is the result of more than three years of research which earned the author a doctoral degree at the Ludwig-Maximilians-Universität Munich. Philipp Sandner's studies of patent and trademark portfolios are a remarkable contribution to the field. I am sure that these results will find the attention of practitioners and researchers alike.

Munich, July 2009
Prof. Dietmar Harhoff, Ph.D.

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This dissertation would not have been completed without the help of faculty members, my friends, and my family. I would like to express my gratitude to these individuals for their assistance and their support. Several deserve special mention.

I first read about Professor Dietmar Harhoff and his research institute, the Institute for Innovation Research, Technology Management and Entrepreneurship (INNO-tec), while writing my diploma thesis in 2005. At that time, I did not expect to write a dissertation at his institute or to become a member of the staff at the Ludwig-Maximilians-Universität München. But this is exactly what happened, and it has shaped my life in a very fortunate way. As my doctoral advisor, Professor Harhoff provided me with numerous opportunities to learn more about management, economics, and research. He encouraged me to question and to reflect upon various social science phenomena. This has not only sharpened my mind but has allowed me to immerse myself in science and understand academic pursuits. Professor Harhoff has been a supportive advisor throughout my career at the Ludwig-Maximilians-Universität in Munich, always demonstrating his faith in both my lecturing capability and research projects. I also wish to thank him for making it possible for me to stay at the University of California at Berkeley while writing my dissertation.

I am also grateful to Professor Tobias Kretschmer, my second advisor, for his excellent and motivating support. I benefited greatly from his research experience, his understanding, and his warmth. Our numerous discussions deepened my understanding of economic problems, and his confidence in my work has been very motivating.

Professor Georg von Graevenitz helped me immeasurably with my ‘academic socialization’. Not only has he always been a strong advocate for me but he has also been generous with his time and his insights. He shared his knowledge of conceptualization and establishing scientific evidence, which enormously impacted this particular project. His logic has guided my more modest attempts to investigate the economic role of intellectual property rights. I want to thank Georg for his unflagging encouragement and for boosting my confidence by providing me with opportunities and giving me an equal voice in our work together.

Through his efforts in our Master of Business Research classes, Professor Ralph Elsas inspired me to think about the fundamentals of quantitative empirical analysis. He opened up new horizons by teaching me how to simulate and assess estimation techniques. This knowledge promises to influence my future work.

I am very fortunate to know Karin Hoisl. On numerous occasions, she encouraged me to initiate the variety of independent work required for a doctoral thesis. Karin has been a wonderful source of advice for me during crucial decisions in the last few years. She always took time from her schedule to help me.

I met Jörn Block a few weeks after beginning work on my dissertation and soon realized that we thought the same way about academia and economic phenomena. He has always encouraged my work and has been a tremendous resource for discussing various issues. His opinions and his willingness to share them have been great assets. Jörn has always been willing to invest his time and energy in improving others' work. Writing with Jörn has been one of the great learning experiences and most enjoyable work experiences of my doctoral studies.

Despite having known Richard Weber for only a short time, his opinions and his thoughts have had a lasting effect on the way I think about work and research in business and economics. Richard's willingness to discuss research issues as well as his efforts to improve the quality of this dissertation, demonstrate a dedication to both research and friendship. I know that I can always count on him for a well-reasoned opinion.

I am grateful to Roland Stürz for helping me with the tone and discipline of my writing. His constructive criticism during the course of this dissertation has been very helpful. Moreover, his ability to survive the administrative 'machinery' of the university with a good sense of humor has served as a model to me.

Both Thomas von Eggelkraut-Gottanka and Lars Ullerich set a wonderful example of grace and good humor. I shared an office and many great conversations with Lars Ullerich. He always provided an intelligent, clear-headed perspective on academic and personal issues. Thomas always listened when I needed to talk. The care, discipline, and organization that he brings to his work have benefited my way of working. I thank both Thomas and Lars for their counsel and friendship.

I also would like to thank Ulrich Lossen, who took charge of me during the first few months of my doctoral studies. Although he may not have realized it at that time, he also provided me with the adequate training for my dissertation years.

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I want to thank the good friends that I have made in Munich and elsewhere for their support throughout my time as a doctoral student. In particular, conversations with Michael Bendels, Martin Jaron, Dennis Johannßen, and Johannes Minho Roth have helped me to overcome the inevitable problems one encounters in writing a dissertation.

I also gratefully acknowledge the institutional support that I received while working on this project. In particular, I thank the Ludwig-Maximilians-Universität in Munich and the German Research Foundation (Deutsche Forschungsgemeinschaft) for providing me with scientific opportunities and economic support. The University of Mannheim, where I graduated, provided me with a solid education, from which I could to draw upon for both lecturing and research. I am particularly grateful to Professor Peter Milling, who taught me how to think about management problems. He also gave me an early push at his research institute, which had a significant impact on my decision to engage in a doctoral thesis. I owe a special debt to Prof. Stuart Graham and Prof. Ted Sichelman at the Berkeley Center for Law & Technology for hosting me as I worked on this dissertation at the University of California at Berkeley. I also thank the Office for Harmonization in the Internal Market in Alicante for providing the data used in this dissertation.

Above all, I wish to thank my family, especially my parents, my sister, and my girlfriend Annika for their love, sacrifice, and kind indulgence. They supported me every day, always believed in me, and continued to be interested in my work. Now that my dissertation is finished, my enthusiasm and excitement as well as my displeasure on seldom occasions, have conflated into rich personal experiences and rewards.

Philipp Sandner

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List of Abbreviations

Art.	Article
BoA	Boards of Appeal
CFI	Court of First Instance
CTM	Community Trademark
e.g.	exempli gratia
ECJ	European Court of Justice
EPC	European Patent Convention
EPO	European Patent Office
EU	European Union
i.e.	id est
IAS	International Accounting Standards
INPI	Institut national de la propriété industrielle
IP	intellectual property
IPC	International Patent Classification
ISI	Fraunhofer Institute of Systems and Innovation Research
MSCI	Morgan Stanley Capital International
NLLS	non-linear least squares
OHIM	Office for Harmonization in the Internal Market
OLS	ordinary least squares
p.	page
p.a.	per annum
pp.	pages
QAP	Quadratic Assignment Procedure
OST	Observatoire des sciences and des techniques
R&D	research and development
SIC	Standard Industrial Classification
UK	United Kingdom
US	United States of America
WIPO	World Intellectual Property Organization
WTO	World Trade Organization

1 Introduction

1.1 Motivation

As intangible assets have become increasingly important (Zingales, 2000), the importance of physical assets for company performance has decreased over the last few decades. Intangibles refer to companies' assets that lack a physical embodiment. They can be defined as "any factors of production or specialized resources that permit the company to earn cash flows in excess of the return on tangible assets" (Simon and Sullivan, 1993, p. 31). Intangible assets can take various forms and may be partly protected by legal rights. Knowledge assets, which are technology-related intangibles, are accumulated through investments in research and development (R&D) and may be protected through intellectual property (IP) rights such as patents or utility models (e.g., Hall, 1993b; Hall *et al.*, 2005). Brand assets[1] belong to market-based intangibles and can be built through advertising investments and be protected through trademarks[2] (e.g., Mendonça *et al.*, 2004; Srivastava *et al.*, 1998). Besides technology- and market-based assets, intangibles can also occur in other domains such as human capital, partnerships, or supplier relationships (Lev, 2001). As intangible assets are important in various company operations and processes, it becomes clear that they have the potential to "augment the earning power of a firm's physical assets" (Simon and Sullivan, 1993, p. 31). According to Ross (1983), assets reported in accounting

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1 The term 'brand assets' is used in this dissertation to highlight the existence of different classes of intangible assets a company can invest in: e.g., knowledge assets as technology-based assets and brand assets as market-based assets. Note that the term 'brand equity' used in the marketing literature (e.g., Aaker, 1991; Ailawadi *et al.*, 2003; Simon and Sullivan, 1993; Srinivasan *et al.*, 2005) could be employed interchangeably because its meaning is virtually congruent. However, I prefer 'brand assets' over 'brand equity' for the following reason: Companies' balance sheets report assets (such as property, plants, equipment, cash, or cash equivalents) and liabilities (such as equity of common stocks, other components of equity, short-term debt, or long-term debt). On the one hand, the clear similarities between brands and assets cannot be overseen because, for example, both are owned by a company. On the other hand, the analogies between brands and equity are limited, in particular because equity as an accounting item belongs to liabilities on balance sheets.

2 In this dissertation, I use the spelling 'trademark' rather than 'trade mark'. 'Trademark' is the common spelling in the United States of America (US) and in international institutions such as the World Intellectual Property Organization (WIPO) and the World Trade Organization (WTO). 'Trade mark' is normally used in the European Union (EU) and in many of the countries formerly belonging to the Commonwealth.

strongly deviate from the ‘real’ value of a company, its market value. That is because the latter also encompasses intangible assets largely not captured by accounting measures.

Despite their importance, intangible assets are rather difficult to measure because present accounting techniques have difficulty determining the financial value of these assets (Lev, 2001). Efforts to build intangible assets such as investments in R&D or advertising are normally not capitalized and are thus not carried forward as assets in companies’ balance sheets (Hall and Oriani, 2006; Ross, 1983). According to the International Accounting Standards (IAS), the capitalization of R&D and advertising investments is rather restrictive (Ballwieser, 2006). Precisely, research costs are always charged to expense (see IAS 38.54). Development costs may be capitalized when certain requirements such as the technical and commercial feasibility and the intention to actually market the product are met (see IAS 38.57). Advertising expenditures cannot be capitalized at all (see IAS 38.63 and IAS 38.69c). Although their benefits last longer than the accounting period, the efforts that create companies’ intangible assets are largely reported as expenditures in annual income statements. Overall, accounting measures inadequately assess companies’ intangible assets.

The difficulties of formal reporting structures to capture the value of intangible assets are contrasted with the importance of assessing intangible assets for analysts inside and outside companies. This leads to the need to comprehensively measure and assess intangibles. Although formal reporting structures to assess intangible assets are largely absent, financial market investors appraise companies daily to make appropriate investment decisions and to direct their funds. This allows financial markets to serve as an independent source of company evaluation (Ross, 1983). Investors make comprehensive and seemingly objective assessments of companies’ assets in order to examine companies’ potential future performance. They analyze companies as bundles of assets and appraise both tangible and intangible assets. Intangible assets are created by companies’ decisions such as investments in R&D to develop a new technology or investments in advertising to build a brand. Investors are confronted with assessing the consequences of these decisions when they analyze annual statements, press releases, or the potential success of companies’ products.

Linking information on companies' assets to their value in financial markets has thus allowed researchers to approach and examine intangible assets. However, different strands of literature have focused either on knowledge assets or on brand assets. Only few studies have jointly integrated several domains of intangible assets. The economics literature has investigated knowledge assets using R&D investments or data on patents. Some studies have focused solely on R&D investments (e.g., Hall and Oriani, 2006; Toivanen *et al.*, 2002) while others have utilized patent data (e.g., Blundell *et al.*, 1999). Some studies used both R&D and patents to estimate the economic value of technological assets (e.g., Griliches, 1981; Hall, 1993b; Hall *et al.*, 2005). To account for the greatly dispersed distribution of patent value, research has applied quality indicators such as patent citations (e.g., Bloom and van Reenen, 2002; Hall *et al.*, 2005). All of these studies present a positive relationship between knowledge assets and company values in financial markets.

In the marketing literature, brand assets have been intensely studied as intangible assets with researchers relying on advertising efforts or on brand characteristics (e.g., Rao *et al.*, 2004; Simon and Sullivan, 1993). To a large extent, marketing research that deals with market-based assets is concerned with corporate brand management and how the decisions involved therein affect the value of brand assets. Most studies examining brand assets take a consumer perspective and investigate the conditions under which consumers are attracted to brands. This is then attributed to the brand strength and, therefore, assumed to affect the value of brands. Fewer studies take an objective approach by relating brands to financial markets in order to assess their earning power as intangible assets (e.g., Barth *et al.*, 1998; Kallapur and Kwan, 2004; Lane and Jacobson, 1995; Rao *et al.*, 2004; Simon and Sullivan, 1993). Lane and Jacobsen (1995), for example, link company values in financial markets to decisions in corporate brand management and show that stock markets react to announcements of brand management. Another example is Rao *et al.* (2004) who employed a Tobin's *q* format to demonstrate how different kinds of branding strategies are associated with company values in financial markets.

Neither stream of literature has given trademarks a prominent role in investigating intantible assets. On the one hand, trademarks and brands are obviously strongly linked (Mendonça *et al.*, 2004), but the marketing-related body of literature neglected trademarks as fundamentals and legal anchors of brands. This is surprising because these very IP rights are the only reason why companies are able to protect their brands and to control them from drifting away. It is the trademarks with the legal instruments they provide that allow their owners to prevent others from unauthorized use (European Council, 1993, Art. 9). On the other hand, there exist only tentative attempts in IP-related work to investigate trademarks and the intangible assets they protect (i.e., brand assets). A notable example that assesses the value of trademarks is the study performed by Greenhalgh and Rogers (2006a). They found that trademark activity is positively associated with companies' stock valuations although they do not account for the great dispersion in the value of trademarks. Despite the prevalence of trademark rights in all areas of business, there is a lack of studying them. This lack concerns both the business literature (i.e., from a brand perspective) and the economics literature (i.e., from an IP perspective). In addition to that, there are only very few studies that *jointly* investigate technology- and market-related intangibles although investors in financial markets obviously consider companies as entities that own various types of intangible assets.

This dissertation aims to investigate the valuation of both technology- and market-based intantible assets and, furthermore, to tackle the divergence between the value of companies' physical assets and the valuations of companies in financial markets. While previous research mostly examined knowledge assets and brand assets separately, the present work seeks to consider both technology- and market-related assets simultaneously. I explicitly focus on companies' IP portfolios in my investigations but also rely on monetary measures such as R&D or advertising investments. The IP rights I consider are patents and trademarks. However, I place special emphasis on the latter for the following reasons. Research on patents has a rather long history in assessing intangibles (e.g., Griliches, 1981; Cockburn and Griliches, 1988). Trademarks and, in particular, their firm-level portfolios have largely been neglected by researchers in the area of both business and economics. While patents are formidable instruments for investigating companies' technologies, trademarks are potentially in the same position to examine companies' market-based assets. This is reasonable as practice shows that numerous trademarks have existed for generations and have long guided and continue to guide product choice (e.g., Swaminathan *et al.*, 2001). In other words, the world today is unimaginable without trademarks that transmit messages or deliver value propositions to assist or influence us when we decide to purchase products. This is why I believe that, when assessing intangibles, such market-based assets should have an equal role relative to technology-based assets although the marketing literature seemingly neglects this IP right as the legal backing of brands. Thus, I seek to analyze both domains of IP rights jointly in order to unveil the importance of both patents and trademarks when examining intangibles.

This dissertation seeks to contribute to the existing literature in the following ways. First, it aims at providing evidence that both patents and trademarks are financially valued. Evidence concerning the valuation of patents has been established by previous research (e.g., Griliches, 1981; Cockburn and Griliches, 1988; Hall *et al.*, 2005). Regarding patents, this dissertation therefore aims at substantiating the evidence from other work that it is not the pure number of patents a company possesses that are valued but their quality. Concerning trademarks, I seek to provide evidence that their value is also widely distributed. Furthermore, a main contribution of this dissertation is to carve out indicators of trademark value that can be employed on a large scale to account for trademarks' dispersed value. Because the market value approach provides a proven framework in the literature, I build on this methodology and extend it to accommodate trademarks.

Second, I demonstrate that the trademarks a company owns are not a loose accumulation of legal rights. Instead, this dissertation seeks to show that trademark portfolios have an inherent logic and are to a large extent systematically built. A technique that reveals the structure of trademark portfolios will unveil the different roles of trademarks as well as the filing strategies responsible for producing these portfolios. This technique shows that trademark portfolios are organized in families that coherently protect brands. This is an important contribution as it makes the association between brands and trademarks explicit. Revealing the structure of trademark portfolios adds to the few studies in economics that simply pool trademarks on the firm-level (Bosworth and Rogers, 2001; Greenhalgh and Rogers, 2006a, 2006b). Also, it complements marketing-related research (e.g., Rao *et al.*, 2004; Simon and Sullivan, 1993) by investigating brand assets through entire trademark portfolios obtained from objective data sources. Concerning marketing-related research, this contribution is particularly noteworthy since a large share of work studying brand assets deals with hypothetical data from laboratory settings or subjective data from consumer evaluations (e.g., Aaker and Keller, 1990; Dacin and Smith, 1994).

Third, when examining intangibles using company values in financial markets as independent measures of valuation, it is necessary to record company values at discrete points in time usually following annual periods. Such annual observations have regularly been used when applying the market value approach (e.g., Hall *et al.*, 2005; Hall *et al.*, 2007). I follow this approach but also seek to provide additional evidence that relies on continuous patterns of stock movement. Assessing patterns of stock movement complements the rather common market value approach, which rests upon periodical observations, because financial markets are subject to disturbances over the course of the year on a monthly or even a daily basis. This dissertation contributes to research on the valuation of intangible assets in that it employs two complementary approaches to carve out the importance of both technology- and market-based intangibles. It also adds to research on stock comovement which is a well studied topic in finance (e.g., Barberis *et al.*, 2005; Pindyck and Rotemberg, 1993; Shiller, 1989; Zuckerman and Rao, 2004). However, finance scholars have always analyzed companies' fundamentals with monetary measures instead of using other data to examine the underlying intangibles that produced these monetary measures.

This dissertation aims at contributing to a better understanding of how IP rights and their firm-level portfolios reflect and protect companies' intangible assets. I seek to provide evidence that IP rights are capable of delivering novel insights about technology- and market-based intangibles and, also, about their valuation in financial markets. In other words, the link between financial markets, patents, and trademarks is assessed. Still, the focus on trademarks also allows stating another objective, namely the promotion of the role of trademarks so that this category of IP rights might eventually achieve some of the relevance patents already have in research.

1.2 Structure of the Dissertation

This dissertation consists of an introduction to the European trademark system (Chapter 2), three empirical analyses dealing with the link between IP portfolios and financial markets (Chapter 3 through Chapter 5) and a conclusion (Chapter 6).[3] Of the empirical analyses, the first and second deal with the valuation of companies' technology- and market-based assets while the third examines how patterns of stock movement can be traced back to these assets. The evidence provided in this dissertation draws upon European IP rights, namely 'Community Trade Marks' (CTMs) filed with the Office for Harmonization in the Internal Market (OHIM) in Alicante and 'European Patents' filed with the European Patent Office (EPO) in Munich. As both European and non-European companies file substantial amounts of both CTMs and European Patents, the set of companies is not restricted to those that are European. In other words, I examine the worlds' largest companies and their IP positions in Europe.

In Chapter 2, I describe the European trademark system. I believe this presentation is important since, with the exception of very few studies (e.g., Greenhalgh and Rogers, 2006a; von Graevenitz, 2007), CTMs as pan-EU trademark rights have not been used in empirical research. I explain the requirements of trademark registration and map the process from filing trademark applications with the OHIM to their registration. I also explain the legal actions available to owners of trademarks that allow them to attack competitors' branding aspirations and stop the actions of rivals that seek to unfairly appropriate the value of the trademarks owned. In contrast to European Patents, CTMs have not been empirically analyzed on a large scale. I therefore present descriptive statistics of the CTM database provided by the OHIM, which is basically a copy of the CTM register. This provides insights into the structure and processes of the European trademark system administered by the OHIM.

3 For the following reason, the European trademark system is described in this dissertation but a similar presentation of the European patent system is omitted. Taking an economic perspective, Guellec and van Pottelsberghe de la Potterie (2007) provide an extensive description of the European patent system. An analogous description of the European trademark system also highlighting economic issues does to my knowledge not exist.

The purpose of Chapter 3 is to investigate the contribution of R&D investments, patents, and trademarks to the market values of companies using a Tobin's *q* format. I employ non-linear least squares (NLLS) regression techniques to estimate the market value equation for 1,216 companies. The results show that trademarks, which have rarely been examined in previous research, play an important role in determining a company's valuation. Indicators derived from publicly available trademark data are shown to reflect trademark value. Knowledge assets are also valued in financial markets but patents need to be adjusted for their value to be informative. Trademark portfolios are found to represent 8.1% of the firm value while patent portfolios capture 4.7% and R&D investments 19.9%. These insights add to our understanding of how firms are valued and how important it is for companies to actively cultivate their IP base.

Chapter 4 uses trademarks to explore brands as intangible assets. Trademarks protect brands and make them visible. Brand management decisions can therefore be observed through trademarks. Corporate brand management deals with the allocation of brands and products because there are no 1-to-1 relationships between them. Instead, brands can encompass multiple products. When new products are introduced, brand management deals with decisions to either create new brands or use existing ones. Such decisions require trademark filings which reflect both the creation of new brands as well as the development of existing brands through hedging, modernization, and extension. I develop and apply a technique that reveals the inherent structure of trademark portfolios. This allows an assessment of how brands are protected by trademarks and how trademark filing strategies produced these portfolios. In this chapter, a cross-sectional dataset of 1,735 companies is compiled and, again, the market value approach and NLLS estimation is used to assess how companies benefit from employing different trademark filing strategies. The results show that financial markets value the gradual development of brands while the creation of brands is not financially valued. These results are explained by the cash flow potential of brand development. Future cash flows can be expected, first, when companies re-use existing brands to introduce new products and, second, when companies coherently and further develop previously established brands rather than creating numerous new ones.

Chapter 5 examines patterns of stock comovements. This permits an investigation to what extent both technology- and market-based assets are associated with patterns of monthly, weekly, and daily movements of companies' stock prices in financial markets. To conduct this examination, I analyze dyads of companies.[4] More specifically, I form pairs of companies and assess the comovement of their stocks, i.e., the degree of synchronous movements within each pair of stocks. Then, the comovement of stocks within each pair is related to the similarity between the paired companies. Similarity is assessed on two dimensions: companies' technological activities measured by patents and their activities in the product market measured by trademarks. Drawing on 14,520 company pairs, I find that both dimensions of proximity add value in explaining stock comovement. This suggests that IP portfolios are capable of informing investors in financial markets about companies' technology- and market-based assets. Moreover, evidence is found that both patents and trademarks add additional value over industry categories although the aim of industry classifications themselves is to form coherent groups of companies. Therefore, I argue that the approach of relying on IP portfolios to assess companies' assets might free investors and researchers from their strong attachment to discrete industry classifications because both patents and trademarks provide valuable information about companies' assets.

Chapter 6 concludes this dissertation and highlights the key findings. It also provides an outlook which prominent role IP rights might play in further research on intangible assets.

[4] Dyadic datasets contain pairs of entities. Accordingly, a company dyad is a pair of companies.

2 The European Trademark System

The European trademark system refers to the unitary trademark right which exists for the entire territory comprising the member states of the European Union (EU) (European Council, 1993, Art. 1).[5] The pan-EU trademark right is named 'Community Trade Mark' (CTM). It has existed since 1996, coexisting with the national trademark regimes of the member states of the EU. Since very few studies in economics and the business literature have dealt with CTMs and the European trademark system (Mendonça *et al.*, 2004), the aim of this chapter is to describe the CTM system and to provide some descriptive statistics to corroborate the role of CTMs in the course of trade.

First, Section 2.1 presents the role of trademarks for companies. Next, Section 2.2 portrays the institutional structure of Europe's trademark system while Section 2.3 describes the process from trademark application to trademark registration. In Section 2.4, I explain the requirements of trademark registration. Trademarks can be challenged by competitors before and after they have been granted. I describe these legal mechanisms in Section 2.5. The database obtained from the OHIM which basically is a copy of the CTM register is described in Section 2.6.[6]

2.1 The Role of Trademarks for Companies

The role of trademarks for companies can be divided in two functions. First, trademarks can be viewed as commerial links between companies and consumers that allow companies to transmit information. Second, trademarks allow consumers to distinguish between products that carry different trademarks thereby facilitating product identification. Both functions of trademarks are described below.

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5 From 2007 on, the territory of the 27 EU member states is covered by this unitary trademark right.

6 The empirical studies in Chapter 3 through Chapter 5 draw upon these data.

2.1.1 The Function of Information Transmission

Companies use trademarks as commercial links which connect the companies that own them with their present and prospective consumers. By using a trademark, a company aims to establish a direct commercial connection by which messages can be transmitted to consumers. Consumers perceive the trademarks attached to products and use them for product identification. Trademarks facilitate or ease consumers' product choices by transferring information and acting as a vehicle for reducing perceived risk (Economides, 1988; Montgomery and Wernerfelt, 1992; Wernerfelt, 1988). In turn, these 'direct links' to customers allow a company to build its reputation and benefit from customer loyalty. These explanations also apply to brands which are highly related to trademarks (Mendonça *et al.*, 2004). Trademarks are rooted in law while brands are a business concept. Brands may combine a set of values employing signs or symbols in order to convey them. These signs or symbols and their commercial use are typically encompassed by trademarks. By registering trademarks and 'marking' its products or services, companies aim at making a name, a slogan, a figure, or a shape visible in the market place. Nevertheless, if products are sold under a brand, rather often a bundle of multiple trademark rights is used (Mendonça *et al.*, 2004).[7] Thus, trademarks represent the legal building blocks upon which a brand may be built. Put differently, a brand needs legally protected signs to carry its values. The trademarks owned by a company can therefore be viewed as its visible front-end.

As Economides (1988) points out, trademark protection allows companies to offer products whose qualities may not be assessed by consumers before purchasing or using them. Products with such characteristics are also known as experience goods and are best explained when comparing them to search goods. The difference between search and experience goods is based on the point in time at which the consumer is able to determine the quality of the purchased product (Cabral, 2000a; Nelson, 1970; Tirole, 2003). With search goods, consumers are able to evaluate the product's quality before actually purchasing it. The features of a personal computer, for example, may be assessed before it is bought. Experience goods require the consumer to first buy the product before its quality can be determined because only consumption of the product will enable the consumer to assess its quality. Here, a consumer can use the experience from repeated purchases for future decisions. Examples include the quality of a restaurant or the taste of wine. In addition to search and experience goods, Darby and Karni

[7] A good example is *IBM* which filed several CTMs with the OHIM. Some of these CTMs protect the abbreviation *IBM* as a word mark while others protect the logo.

(1973) introduced the notion of credence goods. Credence goods do not, or only rarely, allow the consumer to determine quality as it is the case for medical or legal services. Consumers face an asymmetric information problem when purchasing goods with experience or credence characteristics. They will only learn about the product quality, if at all, after the product has been purchased. In this case of asymmetric information, companies that use well-known trademarks to mark their products may benefit from a leap of faith due to the consumer perception attributed to the trademark or associated brand. Trademarks function as carriers of information about products and reduce the search costs of prospective consumers (Economides, 1988). Hence, as a means of simplification, trademarks substitute for more complex ways of obtaining information about products. The underlying mechanism is that trademarks connect past consumption, present choice, as well as several products marketed under the same brand. An interesting example is the case of brand extensions (Broniarczyk and Alba, 1994; Cabral, 2000b; Choi, 1998; Montgomery and Wernerfelt, 1992; Wernerfelt, 1988): If a firm attaches a known trademark to a new product, it seeks to reduce search costs by tapping into previously available knowledge in order to infer the quality of the new product. As a vehicle of information transmission, trademarks can also transfer the emotional identity or the image of a brand.

Transferring information via trademarks is only possible if consumers are able to distinguish between several trademarks. This corresponds to the function of product identification, which is described in the next section.

2.1.2 The Function of Product Identification

The advent of protection by means of trademarks is usually traced back to medieval times, when badges where attached to objects to discriminate between the origins of these objects (Besen and Raskind, 1991). Since that time, the relevance of identifying the source of a product has diminished. Instead of using trademarks to identify a product's source, the role of trademarks has shifted to the identification of the products itself. Today, trademarks are primarily intended to identify products and differentiate these products from those of competing firms. This more abstract and pure function of product identification has important implications for companies' business models because trademarks in principle allow a company to decouple production and marketing processes. Nowadays, a retailer, franchisee, licensee, or importer, although not being the producing source, may be authorized to attach trademarks to a product in order to signal identification to consumers (Thomas, 1981). In an extreme case, a separation between manufacturing and marketing, facilitated by trademarks, could even lead to situations in which the manufacturing entity of a product could be more or less arbitrarily exchanged with another entity. Such situations might occur, for example, when operations are moved from one country to another without consumers taking notice.

The function of product identification focuses on differentiating one product labeled with a trademark from those of competitors (Phillips, 2003). Trademarks can serve only as direct links between companies and consumers if communication and information transmission via trademarks is not interfered with by competitors. A consumer's perception of a trademark would become diluted if competitors were allowed to use identical or confusingly similar trademarks for their own products. To fulfill their function of identifying products, trademarks must allow consumers to be in the position of differentiating between products marketed by several companies. For this reason, distinctiveness is a legal requirement for registering a new trademark (European Council, 1993, Art. 4, and Art. 7).

Assume that two products from two companies are identical apart from the different trademarks they carry as identifiers. According to Cabral (2000a, p. 217), "it does not matter whether products are physically differentiated or not, so long as consumers treat them as different." The legal concept of distinctiveness ensures that consumers at least perceive these otherwise identical products differently. Trademark law embodies and provides mechanisms for proprietors and competitors that ensure trademarks to be inherently distinctive enough to allow for product differentiation. Precisely, the concept of distinctiveness unfolds in two ways. First, differentiation can be achieved because the holder of a registered trademark may prevent others from infringing it (i.e., from unfairly appropriating the value of an established trademark) (European Council, 1993, Art. 9). Second, distinctiveness provides a legal ground for opposing a rival's trademark application if it is confusingly similar to the trademark owned (European Council, 1993, Art. 8). Both ways of putting distinctiveness into practice can be traced back to the aim of the trademark system to provide undistorted competition between rivals (Phillips, 2003).

The legislator sets the legal framework in which companies engage in trademark activities. How the trademark system in Europe has been set up is described in the next section.

2.2 The Structure of the European Trademark System

To describe the structure of the European trademark system, it is important to address the justification for this body of law. The need to minimize unfair exploitation and detrimental activities between competitors has resulted in a trademark law which seeks to provide undistorted competition between rivals. This is only possible when the communication between a company and its consumers remains free from interference (Phillips, 2003). Therefore, trademark law regulates the coexistence of trademark owners and the balance of interests between them, their competitors, and their consumers. These principles and their implementation govern trademark law, and thus the ability of companies to secure their assets and recover the costs incurred from researching new technologies, developing new products, and supplying customers.

The legal protection conferred by a trademark right is geographically limited according to the authority granting this right. This principle of territoriality is one of the traditional and ubiquitous characteristics of each system of IP rights. Put differently, this feature of trademark (and also patent) rights geographically limits the validity of an IP right. Protection was originally coterminous with the borders of the granting jurisdiction. For decades, the tendency towards harmonization has dominated the international development of trademark law (Seville, 2001). International agreements have sought to expand the area of protection and to streamline registration procedures.

The EU sought to harmonize national trademark law through the Council Directive No. 89/104/EEC (European Council, 1988).[8] This harmonization set the groundwork for the creation of the CTM as a pan-EU IP right through Council Regulation 40/94 (European Council, 1993). This regulation established a unitary trademark system with a single procedure and unified rules for the EU territory. The European trademark right system was designed to coexist side by side with the national trademark systems. The OHIM was created to operate the CTM system from 1996 onwards. Since then, it has offered a single application procedure in one language, applying one set of rules and a single fee (Seville, 2001). At the end of 2006, more than 550,000 CTM applications

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8 The situation is comparable to patents. The European Patent Convention (EPC) resulted in setting up the EPO and a gradual harmonization of national patent laws (European Patent Convention, 1973). It is important to note that a European Patent is not a unitary pan-EU right but rather a bundle of national patent rights. Interestingly, the EPC is not a European initiative but a multilateral treaty. Thus, the countries covered by the EPC are not conterminous with the territory of the EU so that Switzerland, for example, is embraced by European Patents but not by CTMs.

were filed and the OHIM had more than 350,000 CTMs in its register.[9] It is anticipated that the CTM system will eventually replace the prevailing national systems due to its efficiency and geographical coverage. Then, the CTM system might act as an encouraging model for the future establishment of a 'Community Patent' (Seville, 2001).

Besides filing CTMs with the OHIM, trademark protection in Europe can also be gained by filing applications at the national or the international level. Despite the existence of CTMs, national trademark regimes continue to exist and confer protection to the territory of a country. The Madrid system, comprised of the Madrid Agreement (WIPO, 1891) and the Madrid Protocol (WIPO, 1989), creates mechanisms for the international registration of trademarks.[10] Although a uniform international right does not exist, applicants can gain global protection in all or a subset of the member countries of the Madrid system. If an applicant seeks to gain international protection, he must file an application at a local trademark office (or at the OHIM) and designate the additional countries in which he wishes to gain protection. This international application is then forwarded to the WIPO which distributes multiple applications to the trademark offices of the designated countries (or regions). In 2006, 13.6% of the CTM filings originated from international applications (OHIM, 2006).

2.3 The Process of Trademark Registration

The process of applying for a European trademark begins with submitting a CTM application to the OHIM. Although most applications become registered untouched, an interactive process often develops between the applicant, the OHIM, and rivals seeking to challenge an application on its way to the register.

Applicants seeking trademark protection file an application for registration with the OHIM to initiate the examination process.[11] The application is verified by OHIM examiners before being granted. By referring to previously existing national or international trademarks, an applicant may claim the seniority of an earlier trademark right for the CTM application (European Council, 1993, Art. 34). This ensures that the

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9 In 2006, registered CTMs filed back in 1996 and 1997, when the OHIM commenced its operations, had to be renewed. Over 75% of these CTMs were renewed for ten more years of protection (OHIM, 2006).

10 The equivalent with patents is the Patent Cooperation Treaty (WIPO, 1970), which enabled applying for protection in a plurality of designated states through the filing of a single patent application.

11 The fee for filing a CTM application including up to three Nice classes amounts to 900 Euros plus 150 Euros for each additional class (when using the paper form for filing). The registration fee is 850 Euros and 150 Euros for each additional class.

applicant continues to enjoy rights already held, allowing for a smooth transition from the country-based trademark system in Europe to a pan-EU regime. If the examiner is satisfied with the application, it is published in the CTM Bulletin (European Council, 1993, Art. 40). Based on the publication of an application, third parties can lodge oppositions against it within a period of three months following the publication (European Council, 1993, Art. 42). If bargaining between the applicant and the opponent does not yield a result and neither party withdraws, the so-called Opposition Division of the OHIM rules whether registration of the trademark will be refused (European Council, 1993, Art. 127). If this is not the case or if no opposition has been lodged, the process is completed by granting the trademark right through registration in the CTM register (European Council, 1993, Art. 45). It is then valid for ten years and the owner thereafter has the possibility to periodically renew it.

The outcome of the registration process is difficult to predict because either an examiner demands clarification or raises objections, or competitors' oppositions induce proceedings.[12] Phillips (2003) writes about both the absolute requirements imposed by trademark law and competitors' opposition activities and states that the trademark "registration process is a refining process in which many weak or unworthy marks […] are sifted out and eliminated by the granting authorities, whittled down by competitors and finally abandoned by their erstwhile champions" (p. 58). This is why the different stages of the application process provide various signals regarding the quality of the underlying application.

Armed with a trademark right, the owner can stop any unlawful use of the protected sign. This protects a firm's investments in product development or advertising against copyists or rivals who seek to take unfair advantage of the value of an established trademark. Specifically, it protects the brand's value and maintains a brand's potential for differentiation. As rights to exclude others from unauthorized use, trademarks are naturally applicable to take legal action against infringers (European Council, 1993, Art. 9). Infringing acts include identical reproduction or counterfeiting of a trademark, the use of similar signs resulting in confusion among consumers, and the weakening of a trademark's reputation.[13] After successful litigation, the trademark holder is entitled

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[12] An excellent example of the interactive nature of such a process is the trademark application for a three-dimensional mark filed by *Kraft Foods*, as recorded in the decision of the Board of Appeal to refuse the application (OHIM, 2002).

[13] Of course, there are also situations in which trademarks may be used by others without infringing on them such as comparative advertising and non-commercial usage.

to injunctive relief, to receive a compensation for lost sales, and to recover the costs incurred (Besen and Raskind, 1991).[14]

Trademark rights are valid in perpetuity if renewed every ten years (European Council, 1993, Art. 46, and Art. 47).[15] However, holding a trademark for an infinite amount of time is not always possible because a registered trademark might be canceled. Revocation is one possible mode of cancelation if a trademark is left unused within a period of five years (European Council, 1993, Art. 50). The other mode of cancelation is based on the invalidity of the trademark if the requirements upon which the right has been conferred have diminished (European Council, 1993, Art. 51).[16]

2.4 Requirements for Registrability

According to the principles of the Council Directive 89/104/EEC and the Council Regulation 40/94, the basic requirements for registrability are threefold (European Council, 1988, 1993): First, a sign for which trademark protection is desired needs to be represented graphically. Second, distinctiveness is required so that consumers are in the position to distinguish a product from those of competing companies. Third, there are so-called absolute grounds for refusal which represent unconditional requirements.

Regarding the first requirement, trademarks can consist of words, names, designs, letters, numerals, and shapes, or any combinations of these elements (European Council, 1993, Art. 4). Expanding the ‘traditional’ categories of word marks and logos is possible because product surfaces, shapes, three-dimensional objects, or simply colors can also be represented graphically. This is also true for sound marks, tastes, gestures, and even motions although a graphical representation is more difficult.[17] In principle, a vast variety of types are possible. Still, applicants almost completely rely on the traditional categories: As Table 1 shows, word marks and figurative signs make up the lion’s share of all CTMs (62.8% and 36.6%, respectively) indicating that other categories are scarcely used. This can be explained by the difficulties associated with repre-

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[14] Note that such complaints have to be lodged with national courts (European Council, 1993, Art. 91) as a European court to settle disputes involving CTMs does not exist.

[15] The renewal fee is 1,500 Euros for a CTM with three or fewer Nice classes (when using the paper form for renewal) and 400 Euros for each additional Nice class.

[16] A cancelation based on invalidity is sometimes also termed annulment or nullity.

[17] For example, sound marks can be graphically represented through musical notations, and gestures through series of drawings.

senting these trademarks graphically and, furthermore, in proving that these trademarks are distinctive.

Table 1: Breakdown by Type of Trademark (1996-2006)

Type of CTM	CTMs	%
Word mark	224,979	62.8%
Figurative mark	130,993	36.6%
Three-dimensional mark	1,976	0.6%
Color mark	103	0.0%
Sound mark	38	0.0%
Hologram mark	3	0.0%
Others	186	0.1%
Total	358,278	100.0%

Source: OHIM (2007).

Concerning the second requirement, the trademark must be capable of allowing consumers to distinguish a given product from those of other firms (European Council, 1993, Art. 4, and Art. 7). Classic examples of trademarks that are inherently registrable are newly invented words such as *Kodak*, *Xerox*, *Polaroid*, *Exxon*, or *Evonik*. Consumer perception is used as a yardstick to diagnose distinctiveness. Relying on consumer perception, signs must be regarded as potential trademarks. In other words, the likelihood of consumer confusion with other symbols or signs is taken as a measure to determine distinctiveness. Due to its unknown character, a newly invented word will not confuse the consumer so that distinctiveness is regularly given. If a sign is not inherently distinguishing at the outset, distinctiveness may also be acquired through use (European Council, 1993, Art. 7). An example is *Manpower*, which is a validly registered trademark although it is basically a word for paraphrasing the workforce of a multitude of workers.

It is important to note that distinctiveness of a trademark needs to be considered in relation to products (European Council, 1993, Art. 38). *Apple* does not qualify for registration in reference to food but is eligible for protection when used for computers and consumer electronics. Confusion is always diagnosed for the average consumer who is considered to be informed, observant, and circumspect (Phillips, 2003). Consumers need to regard a sign as being a trademark which, for example, becomes true when *Apple* is used in connection with computers. Therefore, trademarks are registered for specific product categories represented by the classes specified by the so-called Nice Classification. This international classification system divides the whole product and service space into 45 classes, of which 34 are for manufactured goods and

11 are for services (WIPO, 2006).[18] Applicants must assign an application to one or more classes. Since the applicant must use his trademark in the designated classes to give rivals no cause for revocation requests (European Council, 1993, Art. 50), applicants are prevented from always applying for the total set of Nice classes. Thus, the designation of goods and service classes limits the degree of protection to specific areas (European Council, 1993, Art. 38).

The third requirement concerns absolute grounds for refusal which may only be overcome on rare occasions (European Council, 1993, Art. 7). Reasons for refusal arise if there is something inherently unacceptable in the application. Signs that might need to be used by others are not registrable. Such signs might be publicly reserved terms like currency symbols or geographical indications. These principles ensure that certain signs are not placed under private control. However, a trademark may be registrable if it is a compound containing such signs as elements. This is due to the principle of assessing the trademark as a whole during examination instead of viewing it as single parts.[19] The same applies to generic terms and descriptive words. The former are words from the pool of common vocabulary while the latter are attributes describing the quality of a product. Such words are not registrable for products to which they directly apply.[20] The underlying premise is to keep these words available for general use. Signs devoid of any distinctive character such as barcodes are also not registrable. Policy grounds and consumer deception are further absolute bars to registration. The former prohibits immoral or illegal signs from being registered while the latter safeguards consumers against deceptive marks.[21] It is important to note that some reasons for refusal are only temporary. As described above, this may concern the requirement for distinctiveness which may have been lacking at the outset but can be gained through extensive use (European Council, 1993, Art. 7). Shifts in commercial terminology may also affect the distinctiveness of certain terms. In all, absolute grounds for registration prevent certain words and figures from being registered as trademarks to prohibit unfair monopolization.

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[18] The Nice Classification is regularly revised and is now in its ninth edition (WIPO, 2006).

[19] A good example of a combination is the word mark *Eurohypo* which obviously consists of two common words that cannot be registered when separately filed.

[20] Although *Apple* is generic for apples, it is not for computers and consumer electronics. Once again, it is the perception of the relevant group of consumers that matters.

[21] Interesting examples are trademarks that contain words such as *organic*, *bio*, and *eco*. These words may only be used in trademarks when connected to organic products. Here, the EU seeks to control the use of these words to avoid misleading consumers (European Council, 1991).

2.5 Ways to Challenge Trademarks Before and After Registration

Trademark law seeks to prevent unworthy trademarks from taking root in the register. The OHIM is concerned with ruling out applications not fulfilling the absolute requirements needed to establish a valid trademark right. In contrast and from a relative perspective, companies assist in keeping the register clean by using opposition or cancelation mechanisms. By oppositions, applications which might interfere with previously existing rights can be stalled or stopped on their way to the register. Cancelation of registered trademarks is possible upon invalidity or revocation requests. Invalidity requests aim at canceling trademarks that do not or no longer comply with the registration requirements. Revocation requests seek to eliminate trademarks that are left unused and, thus, fulfill no commercial function. These mechanisms are described below.

Trademark oppositions enable competitors or other third parties to object to an application in order to prevent an applicant from getting its trademark registered (European Council, 1993, Art. 42). An opponent will lodge an opposition if he considers a trademark application to be identical or confusingly similar to his own legally protected right (European Council, 1993, Art. 8). This may be the case if a hostile application seeks to take unfair advantage of the reputation or the distinctive character of the opponent's sign, or is detrimental to it. Owners of earlier rights are therefore able to prevent the unauthorized use of their trademarks. According to the Council Regulation 40/94, these so-called relative grounds for refusal may give reason for non-registrability of an application (European Council, 1993, Art. 8). To initiate the opposition procedure, an opponent has to lodge an opposition with the OHIM.[22] Negotiations between the applicant and the opponent for a settlement as well as the withdrawal of either the application or the opposition are possible at any time. If the parties do not settle their dispute privately, the Opposition Division of the OHIM takes action by agreeing with the opponent and rejecting the application or letting it pass to the register (European Council, 1993, Art. 127). 15% of all filed applications are subject to opposition (see Table 2), and a substantial portion of those receives several oppositions. Only about a fourth of all oppositions are resolved by a decision suggesting that intense negotiations take place between applicants and opponents.

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22 The opposition fee amounts to 350 Euros.

Table 2: Activity in the European Trademark System (1996-2006)

	Until 2006	% of appln.
Applications received	**553,792**	100.0%
Published applications	455,109	82.2%
Opposed applications	83,074	15.0%
Oppositions received	**108,838**	
Opposition resolved (76.3%)	83,007	
Opposition Division of the OHIM takes a decision	23,047	
Without a decision	59,960	
Cancelation requests (invalidity or revocation)	**3,861**	0.7%
Cases closed (72.6%)	2,805	
Cancelation Division of the OHIM takes a decision	2,684	
Without a decision	121	
Appeals before the Boards of Appeals	**9,521**	
Appeals settled (83.9%)	7,990	
Appeals before the Court of First Instance	**524**	
Cases closed (53.6%)	281	
Appeals before the European Court of Justice	**53**	
Cases closed (77.4%)	41	

Source: OHIM (2006).

The opposition procedure may only be invoked by owners of protected signs used in the course of trade prior to opposition (European Council, 1993, Art. 8). Regarding these previously protected signs, opponents mostly refer to trademark rights that are CTMs or national trademarks even though design rights or copyrights also qualify. The previously owned IP rights, to which opponents refer when lodging their opposition (e.g., trademarks, design rights), do not need to be already registered. An application in any countries belonging to the Paris Convention is sufficient.[23] This raises threats to applicants because reasons for potential oppositions may be invisible.

During opposition proceedings, the opposed applicant may request his opponent to demonstrate that his right which has invoked the proceedings is actually used and has become well known (European Council, 1993, Art. 43). As the use of his right must be of significant stature, the opponent needs to provide appropriate evidence such as surveys or advertisements. Naturally, failed proof leads to an immediate rejection of the opposition. As such evidence raises the opponent’s costs, this mechanism assures that firms do not accumulate large portfolios of unused trademarks to control whole areas of commercial terminology. If both parties do not settle by themselves, the

[23] The Paris Convention on the Protection of Industrial Property took place in 1883 and initiated harmonization efforts across countries concerning different types of IP rights (WIPO, 1883). In 2008, the Paris Convention had 173 member states.

Opposition Division of the OHIM rules on how to proceed and explores the trademarks' visual, phonetic, and conceptual similarities, also accounting for the proximity of the products (European Council, 1993, Art. 127; OHIM, 2004). Once again, the likelihood of confusion is the yardstick used to determine whether an application and the opponent's mark are similar. The winning party has the right to recover the costs incurred from the loosing party (European Council, 1993, Art. 81).

Trademark oppositions are related to trademark infringements. To explain this relationship, note that both trademark oppositions and infringements are two sides of the same coin. Both can be traced back to a trademark's right to exclude others from unauthorized use. Infringements inhibit *actual* deployments of a registered trademark while oppositions inhibit *potential* deployments by preventing a rival from establishing a 'nearby' trademark. This has immediate consequences for corporate IP management. If a trademark owner feels threatened, lodging an opposition is the first course of action rather than waiting for the trademark to be registered and to take subsequent action against infringement (von Graevenitz, 2007). As a consequence, a tremendous amount of subsequent infringement proceedings are avoided. Due to the opposition mechanism, a rival's trademark application that is identical or too similar will not find its way to the trademark register (European Council, 1993, Art. 8). Apparently, these opposed signs are unlikely to be used in the course of trade, simply because future infringements apply the same principles governing opposition procedures. As Phillips (2003, p. 425) puts it, the "grounds upon which an application may be rejected are those upon which an infringing act may be prevented."

Trademark oppositions and cancelations are also linked. Both mechanisms seek to destruct the trademark ambitions of rival firms by either hindering an application from becoming a registered trademark (case of oppositions) or by trying to eliminate an unwanted trademark that was previously registered (case of cancelations). It is more difficult to get a rival's trademark expunged from the register than to disrupt the application process since a "granted trademark is presumed valid until the contrary is proved" (Phillips, 2003, p. 426). Naturally, this is reflected in the number of oppositions versus the number of cancelations (see Table 2). Cancelation requests need to be brought before the so-called Cancelation Division of the OHIM (European Council, 1993, Art. 129).

Cancelations can be based on invalidity or revocation. For cancelations upon invalidity, the principles regarding basic registration requirements are applied. If these requirements do not hold anymore, a trademark will be canceled (European Council, 1993, Art. 51). For example, shifts in terminology are addressed when an arbitrary mark starts as a validly registered trademark and, due to its success, becomes a generic term. As a consequence, distinctiveness of this mark is diluted resulting in a loss of trademark protection and in becoming a part of the public domain. Examples from the US where trademarks have become generic terms include *Aspirin* or *Thermos* (Folsom and Teply, 1980).[24] For cancelations following revocation requests, registered trademarks that have been left unused for a period of at least five years can be removed (European Council, 1993, Art. 50). Hence, revocations also prevent companies from collecting large portfolios of unused trademarks.

If an applicant or an opponent is dissatisfied either with the decisions of the examiner, the Opposition Division or the Cancelation Division, complaints may be brought before the Boards of Appeal (BoA) which is also located at the OHIM (European Council, 1993, Art. 58, Art. 61, and Art. 130). By the end of 2006, more than 9,500 appeals were filed (see Table 2). If dissatisfaction persists, appeals against decisions of the BoA may be filed before the Court of First Instance (CFI). This has occurred in approximately 500 cases. To lodge objections against the CFI judgments, complaints must be addressed to the European Court of Justice (ECJ) representing the last instance (about 50 appeals). The precedents brought to the ECJ and the CFI refine trademark law in Europe and develop it further through case law. In turn, this body of law provides guidance and influences applicants' behavior, their strategies, and competition between them.

2.6 Insights into the Trademark Register

In Europe, the list of all trademarks is kept in the publicly accessible CTM register (European Council, 1993, Art. 83). These data include the goods and service classes applied for, dates of the registration procedure, applicant details, and additional information such as seniorities or oppositions. In this dissertation, the CTM register is used as the source of trademark data. Since, with few exceptions, these data have not been used before, this database is briefly described in this section. As the CTM register was obtained from the OHIM, these data are called the OHIM database in the remainder of this dissertation.

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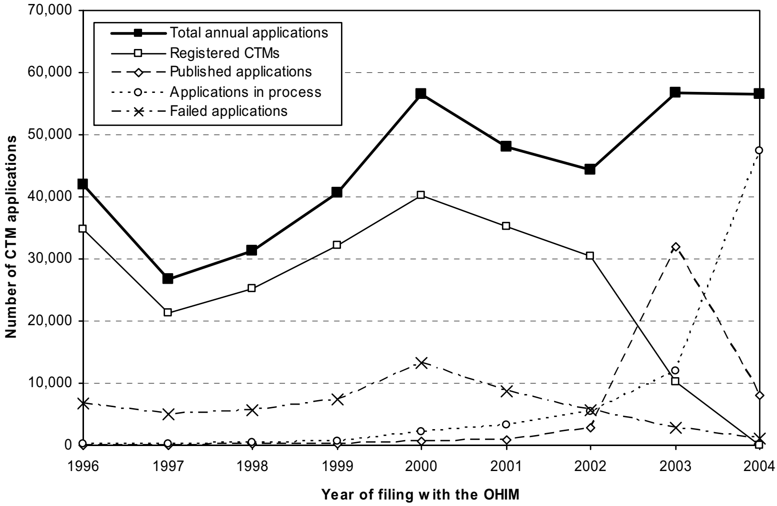
[24] Both examples are interesting as in the EU their trademarks are, in contrast to the US, validly registered. Apparently, both words are perceived differently in the US and the EU. Another interesting example is the verb 'to google'. Recent developments show that this verb, which emerged from the name of the search engine *Google*, also has the potential to become a generic word (Foley, 2006).

The OHIM database contains over 400,000 CTM applications for trademarks filed between 1996 and 2004 of which over 225,000 were registered. Naturally, a substantial share of these applications was still pending at the end of 2004 when the OHIM database and, with it, the legal status of each application was recorded. Figure 1 provides information on the legal status of the trademark applications according to the year of filing. When the OHIM began its operations in 1996, more than 40,000 applications to register CTMs arrived at the office. In 1997, the first year of orderly operations, fewer applications were received, followed by an upward trend.

Figure 1: Annual Applications Filed with the OHIM



An investigation of the legal status shows a peak for failed applications in 2000. The share of failed applications peaked at 23.6% compared to 18.2% in 1999 and 18% in 2001. This is associated with applicants seeking protection for trademarks in service classes, probably due to the internet bubble. Figure 1 shows that the legal status within older cohorts of CTM applications is either registered or failed. More recent cohorts also contain CTM applications that are in process or already published. That is because the OHIM database ends in 2004 and, for some CTM applications, the final outcome of the registration process was not known at that time when the legal status of the applications was recorded. The increasing number of applications in process is associated with a decreasing number of ultimately registered applications. Published applications which have not yet reached a final registration decision peak in 2003. In other words, the grant lag can be observed in the annual distributions of each legal status.

This is important to note because it explains why Chapter 3 and Chapter 5, which both employ registered trademarks, only draw on filings between 1996 and 2002. For these chapters, the data were truncated to account for the duration of the trademark registration process. This differs from Chapter 4, in which no truncation was necessary because this chapter draws on trademark applications.

2.6.1 Applications and Registered Trademarks

Table 3 shows characteristics of the applications that arrived at the OHIM between 1996 and 2004. Regarding the legal status recorded at the end of 2004, 57% of these 402,724 applications have been registered and 13.9% have failed. Note that a substantial share of total applications has not yet received a definite decision. 17.9% of all applications were in process and 11.1% have recently been published. Considering only applications with a definite registration outcome (either failed or registered) allows the computation of an adjusted failure rate of 19.7%. A trademark application fails if the application does not fulfill the registration requirements or if it is successfully opposed. The time frame for taking a trademark application from its arrival at the OHIM to its registration averages out 1.8 years. During that time, opposition proceedings and other registration delays may unfold leading to a maximum of 8.6 years.[25]

Table 3: Descriptive Statistics for Trademark Applications

Variable	Mean	SD	Median	Min.	Max.
Application procedure					
Application failed (dummy)	0.139		0.0	0.0	1.0
Application in process (dummy)	0.179		0.0	0.0	1.0
Application published (dummy)	0.111		0.0	0.0	1.0
Application registered (dummy)	0.570		1.0	0.0	1.0
Examination duration (years) [1]	1.762	0.831	1.460	0.036	8.638
Application characteristics					
Nice classes	2.642	2.473	2.0	0.0 [2]	45.0
Pure product trademark application (dummy)	0.565		1.0	0.0	1.0
Pure service trademark application (dummy)	0.116		0.0	0.0	1.0
Product and service trademark application (dummy)	0.318		0.0	0.0	1.0
Seniorities exist (dummy)	0.096		0.0	0.0	1.0
Number of seniorities	0.398	2.243	0.0	0.0	306.0
Opposed (dummy)	0.144		0.0	0.0	1.0
Number of oppositions received	0.191	0.547	0.0	0.0	20.0

Notes: N = 402,724 trademark applications filed with the OHIM from 1996 to 2004. SD = Standard deviation.
[1] The examination duration refers only to 229,627 applications becoming registered trademarks.
[2] For some of the failed applications, the OHIM removed the initial Nice classes applied for.

[25] The 90th (95th) percentile of the examination duration is 2.7 (3.4) years.

Different characteristics of the trademark applications can be derived from the trademark register. These characteristics are likely to reflect the varying quality of trademark applications and stem from three sources: Nice classes,[26] seniorities, and oppositions. Each application has on average 2.64 Nice classes. Decomposing the spectrum of the 45 goods and service classes set out by the Nice Classification allows one to examine whether trademark applications were filed to protect products alone, services alone, or both. 56.5% of all filings were applications for pure product trademarks. This contrasts with only 11.6% of all applications reflecting pure service trademarks. Mixed applications account for 31.8%.

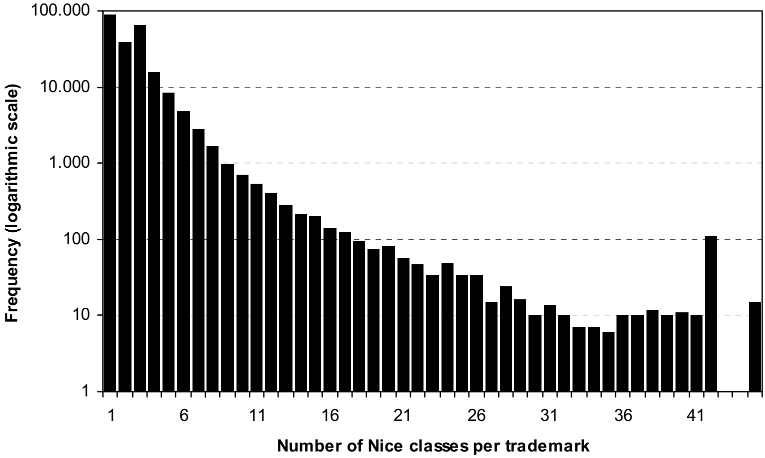
Seniorities account for the number of previous registrations in other jurisdictions and, thus, measure the diffusion and the familiarity of the protected sign prior to the CTM era. Among the seniorities of a CTM, there may be multiple references to the same jurisdiction. The number of seniorities therefore does not measure the geographical coverage of an existing trademark. Instead, it simply refers to the number of previous registrations claimed when the applicant filed the CTM application. At least one seniority is harbored by 9.6% of all applications. Among the trademarks referring to many previous registrations, there are widely known trademarks such as *Shell* (306 seniorities), *Toshiba* (141), and *Panasonic* (132). Examining the high number of seniorities carried by *Shell*, it turns out that 61 seniorities refer to the United Kingdom (UK) and 48 to Portugal. Apparently, CTMs having many seniorities suggest being of higher value due to their prevailing existence when filed with the OHIM.

Recall that oppositions against an application can only be lodged if this 'hostile' application would threaten a previously registered right owned by the opponent (European Council, 1993, Art. 8). Oppositions received can be observed for single applications whereas the number of oppositions lodged is only available at the applicant-level. Among all trademark applications at the OHIM, 14.4% are subject to at least one opposition. At most, CTM applications received 20 oppositions.

[26] The Nice Classification is regularly revised. It is now in its ninth edition (WIPO, 2006). It has 45 classes since its eighth edition which came into force on January 1, 2002 (WIPO, 2001). Before that, the seventh edition was in force which only had 42 classes. Thus, in this dissertation, the variables that build on Nice classes consider 42 classes until the end of 2001 and 45 classes thereafter. It is important to note that the revisions do not concern the overall categorization of trademarks (e.g., in all editions mentioned, class 1 consistently captures all trademarks that protect chemical products). The three service classes (classes 43 to 45) which were added in the eighth edition do not show large application volumes (OHIM, 2007).

To elaborate more on the breadth of trademark protection, Figure 2 depicts the distribution of the number of Nice classes for registered CTMs using with a logarithmic scale.[27] 88,537 registered trademarks (38.6%) award protection for one class. The cost structure instilled in the application rules directly affects trademark statistics (Schmoch, 2003).[28] Thus, trademarks awarded for three classes are more frequent than those awarded for two classes. Trademarks registered for more classes are observed with lower frequencies because trademarks must be used in the Nice classes applied for to give no reason for revocation and, furthermore, because fees rise with the number of Nice classes. An assessment of the signs protected by trademark rights suggests that those with fewer classes tend to protect single products or narrow product lines while trademarks with many classes seem to protect wider product lines or corporate brands.

Figure 2: Distribution of the Number of Nice Classes per Trademark



To assess the protected goods and services in detail, a breakdown into different Nice classes is provided in Table 4. Because a trademark can be affiliated with multiple Nice classes, the sum of affiliations naturally exceeds the number of trademarks.

27 The pattern concerning the frequencies of 42 or more Nice classes per trademark is rooted in a revision of the Nice Classification. The Nice Classification consisted of 42 classes until the end of 2001, and has been extended to 45 classes thereafter. Thus, those trademarks with 42 registered Nice classes or more are awarded to the full breadth of all classes (e.g., the trademark *Nestlé*).

28 Recall that both application and registration fees cover up to three classes. For each additional class, further fees occur.

Table 4: Distribution and Characteristics of Nice Classes

	Name	N	%	Trademarks also assigned to: Services	Goods	Ø growth rate p.a.[1]
Goods classes						
1	Chemicals	12,659	2.1%	27.7%		11.1%
2	Paints, varnishes, and lacquers	4,099	0.7%	27.9%		14.2%
3	Substances for laundry use	16,624	2.8%	23.4%		17.5%
4	Industrial oils and greases	3,238	0.5%	41.2%		16.2%
5	Pharmaceutical and sanitary preparations	20,336	3.5%	20.7%		14.8%
6	Common metals	10,986	1.9%	35.5%		11.8%
7	Machines and machine tools	15,977	2.7%	32.0%		11.3%
8	Hand tools and implements	5,047	0.9%	30.7%		15.0%
9	Scientific apparatus	68,003	11.5%	56.4%		12.8%
10	Medical apparatus	11,106	1.9%	26.8%		12.4%
11	Lighting and heating	12,306	2.1%	32.6%		14.2%
12	Vehicles	10,958	1.9%	36.2%		14.5%
13	Firearms	743	0.1%	52.5%		19.6%
14	Precious metals and jewelry	7,763	1.3%	38.6%		13.3%
15	Musical instruments	1,127	0.2%	49.4%		15.0%
16	Paper, packaging and printing	38,704	6.6%	67.7%		11.6%
17	Rubber and gum	6,894	1.2%	25.8%		11.0%
18	Leather	12,703	2.2%	29.0%		14.5%
19	Building materials	7,594	1.3%	35.1%		14.3%
20	Furniture	10,526	1.8%	31.1%		14.2%
21	Household or kitchen utensils	9,278	1.6%	33.0%		15.9%
22	Ropes, sails, and bags	2,146	0.4%	31.1%		12.1%
23	Yarns and threads for textile use	1,072	0.2%	33.5%		16.1%
24	Textiles and textile goods	7,605	1.3%	30.8%		12.7%
25	Clothing, footwear	27,006	4.6%	33.6%		12.6%
26	Lace, pins, and needles	2,216	0.4%	47.2%		11.5%
27	Materials for covering floors	2,626	0.4%	40.9%		15.1%
28	Games, toys, and decorations	14,933	2.5%	40.6%		15.6%
29	Meat, fish, and vegetables	12,682	2.2%	25.6%		16.8%
30	Coffee, bread, and salt	14,735	2.5%	24.9%		14.7%
31	Agricultural and forestry products	6,982	1.2%	29.4%		14.3%
32	Beers	9,060	1.5%	33.7%		16.9%
33	Alcoholic beverages	9,808	1.7%	24.5%		17.3%
34	Tobacco, matches	2,598	0.4%	36.8%		13.7%
Total of goods classes		400,140	67.9%			
Service classes						
35	Advertising and business management	34,879	5.9%		64.7%	29.8%
36	Insurance and financial services	17,301	2.9%		48.4%	21.4%
37	Building and construction	14,070	2.4%		82.0%	18.4%
38	Telecommunications	21,530	3.7%		74.4%	29.7%
39	Transport	13,316	2.3%		67.1%	20.3%
40	Treatment of materials	5,298	0.9%		81.5%	16.9%
41	Education, sport, and culture	28,128	4.8%		75.8%	20.8%
42	Other services [2]	44,822	7.6%		76.0%	22.0%
42	Scientific, technological, and research [3]	6,254	1.1%		77.9%	-
43	Services for providing food and drink [3]	1,629	0.3%		65.0%	-
44	Medical services [3]	1,313	0.2%		78.1%	-
45	Personal and social services [3]	388	0.1%		56.4%	-
Total of service classes		188,928	32.1%			
Total of all classes		**589,068**	**100%**			

Notes: N = 229,627 registered trademarks (filed with the OHIM between 1996 and 2004).

[1] Average growth rate of the annual application volume from 1997 to 2004.

[2] This row only includes trademarks filed until the end of 2001 because it refers to the seventh edition of the Nice Classification which had 42 classes and was in force until January 1, 2002 (WIPO, 1996). The growth rate concerns the annual application volume from 1997 to 2001.

[3] These rows only include trademarks filed as of 2002 because they refer to the eighth edition of the Nice Classification which had 45 classes and came into force on January 1, 2002 (WIPO, 2001). In this eighth revision, class 42 of the seventh edition was splitted into the classes 42 to 45. Due to this revision, no growth rate was computed.

The most frequent classes for protected goods are 'scientific apparatus' (11.5%), and 'paper, packaging, and printing' (6.6%). Among the service classes most often registered is 'advertising and business management' (5.9%). As each trademark can be awarded to multiple classes, it is informative to examine common patterns of classes applied for, allowing an assessment of product-accompanying services (Schmoch, 2003). For each goods class, I calculate the share of trademarks simultaneously registered in a service class indicating a service affinity of this particular goods class. For service classes, the analogous procedure is carried out. The results are also shown in Table 4. Trademarks in 'paper, packaging, and printing' (67.7%) have the highest service affinity while trademarks in 'pharmaceutical and sanitary preparations' (20.7%) have the lowest. For services, the orientation towards goods is highest for 'building and construction' (82%) compared to 'insurance and financial services' possessing the lowest goods orientation (48.4%). A calculation of the average growth rate of the annual application volume reveals that 'rubber and gum' are the slowest growing class (11%) compared to 'advertising and business management' whose annual application volume increases by 29.8% per year. Altogether, there is considerable heterogeneity between the goods and service classes.

Table 5: Differences Between Registered Trademarks and Failed Applications

Variable	Failed CTM applications (N = 56,169)		Registered CTMs (N = 229,627)		
	Mean	**SD**	**Mean**	**SD**	***p*-value**
Number of Nice classes	2.541	2.247	2.565	2.401	0.030 [1]
Pure product trademark application (dummy)	0.501		0.586		< 0.001 [2]
Pure service trademark application (dummy)	0.157		0.114		< 0.001 [2]
Product and service trademark application (dummy)	0.341		0.299		< 0.001 [2]
Seniorities exist (dummy)	0.030		0.126		< 0.001 [2]
Number of seniorities	0.062	0.599	0.562	2.746	< 0.001 [1]
Opposed (dummy)	0.248		0.111		< 0.001 [2]
Number of oppositions received	0.351	0.743	0.138	0.444	< 0.001 [1]

Notes: A p-value of less than 0.01 means that the null hypothesis (the means of both groups are not significantly different from each other) can be rejected at an error level of less than 1%. SD = Standard deviation.
[1] p-values obtained from the t-test on the equality of means.
[2] p-values obtained from the χ^2-test on the equality of proportions.

A rather profane measure of the quality of trademark applications is the outcome of the examination procedure. Granting an IP right can be interpreted as a reward that attributes higher quality to applications that become registered and lower quality to those refused or withdrawn (see Guellec and van Pottelsberghe de la Potterie (2000) for patents). Therefore, Table 5 shows differences between two groups of trademarks: CTM applications that become registered, and CTM applications that fail. Significant differences regarding the characteristics of the applications are indicated by p-values obtained from t-tests or χ^2-tests. Employing a significance level of 1%,[29] registered trademarks do not bear significantly more Nice classes than failed applications (2.541 vs. 2.565, $p > 0.01$). Yet, the composition of trademarks' Nice classes reveals a significantly higher share of pure product trademarks in the group of registered trademarks. Applications for pure product trademarks are registered more often (0.501 vs. 0.586, $p < 0.001$). Conversely, applications for pure service trademarks or mixed applications are rejected more often (0.157 vs. 0.114, $p < 0.001$ and 0.341 vs. 0.299, $p < 0.001$). Not surprisingly, applications referring to seniorities are more likely to appear in the group of registered CTMs (0.030 vs. 0.126, $p < 0.001$) and have a consistently higher number of seniorities (0.062 vs. 0.562, $p < 0.001$). This is due to the nature of seniorities which indicate previously existing trademark rights. Hence, the trademark exhibits familiarity and has been diffused in the market to some degree. Regarding oppositions, a larger share of failed applications is being attacked (0.248 vs. 0.111, $p < 0.001$). Obviously, these oppositions in part lead to the failure of a trademark. Thus, this adds to the interpretation of oppositions being a considerable risk for applicants. Although oppositions are more frequent in the group of failed applications, they may provide information about trademark value. In a nutshell, the above discussion underpins the assumption that the measures shown can be used to approach some dimensions of trademarks' value. A more detailed assessment of these dimensions follows in Chapter 3.

2.6.2 Trademark Applicants

Having discussed the characteristics of trademarks, I now turn to the 99,924 applicants that have registered these trademarks (see Table 6).[30] The number of trademarks is highly skewed, with nearly two thirds of the applicants holding only one trademark. Therefore, the last two columns of Table 6 refer to smaller subgroups of applicants holding trademark portfolios of larger magnitudes (2,615 applicants with 10 or more trademarks, and 580 applicants holding 25 trademarks or more). This provides interesting insights into the application behavior of different subpopulations of applicants. The applicant size, as proxied by the size of trademark portfolios, exhibits large variation and, thus, includes small- and medium-sized, as well as rather large appli-

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[29] A significance level of 1% is chosen due to the high number of observations.

[30] Table 6 includes all applicants that hold at least one registered trademark. I explicitly do not use the term company or firm but applicant since the internal applicant identifier of the OHIM was used to assign the trademarks to their applicants. Since many companies are represented by different applicant entities, an aggregation of applicants is inevitable if companies are to be analyzed. A technique considering this is used in the following chapters.

cants. The applicant *Konami* filed 1,214 applications representing the maximum application volume. Due to failed applications, this applicant does not hold the largest portfolio of registered trademarks. This is held by *Procter & Gamble* which has 638 registered trademarks. At the applicant-level, the rejection rate at the OHIM is equal to an average of 5% of total applications. This rate increases for applicants with larger portfolios.

Table 6: Descriptive Statistics for Trademark Applicants

	Portfolio size						
	≥1 registered trademarks					≥10	≥25
Variable	**Mean**	**SD**	**Median**	**Min.**	**Max.**	**Mean**	**Mean**
Examination process							
CTM applications	3.167	11.098	1.0	1.0	1,214.0	35.222	86.893
Failed CTM applications	0.304	2.663	0.0	0.0	693.0	3.620	9.255
Share of failed CTM applications	0.050	0.142	0.0	0.0	1.0	0.090	0.090
Share of registered CTMs	0.876	0.223	1.0	0.0	1.0	0.738	0.707
Trademark portfolio							
CTMs (= registered trademarks)	2.298	6.845	1.0	1.0	638.0	23.662	57.047
Nice classes / CTMs	2.576	1.971	2.0	1.0	45.0	2.529	2.469
Share of pure product CTMs	0.539		1.0	0.0	1.0	0.651	0.672
Share of pure service CTMs	0.134		0.0	0.0	1.0	0.092	0.081
Share of product and service CTMs	0.326		0.0	0.0	1.0	0.258	0.247
Seniorities / CTMs	0.477	2.494	0.0	0.0	489.0	0.847	1.081
Oppositions brought / CTMs	0.007	0.082	0.0	0.0	6.2	0.048	0.099
Oppositions received / CTMs	0.238	0.605	0.0	0.0	20.0	0.272	0.280
Country of applicant							
US	0.197		0.0	0.0	1.0	0.305	0.334
Germany	0.154		0.0	0.0	1.0	0.176	0.183
UK	0.126		0.0	0.0	1.0	0.126	0.112
Spain	0.094		0.0	0.0	1.0	0.040	0.028
Italy	0.093		0.0	0.0	1.0	0.059	0.053
France	0.071		0.0	0.0	1.0	0.054	0.048
The Netherlands	0.026		0.0	0.0	1.0	0.025	0.026
Sweden	0.027		0.0	0.0	1.0	0.018	0.017
Belgium	0.018		0.0	0.0	1.0	0.013	0.016
Austria	0.016		0.0	0.0	1.0	0.013	0.012
Switzerland	0.016		0.0	0.0	1.0	0.024	0.034
Denmark	0.016		0.0	0.0	1.0	0.021	0.010
Canada	0.014		0.0	0.0	1.0	0.007	0.005
Japan	0.016		0.0	0.0	1.0	0.049	0.066
Other countries	0.117		0.0	0.0	1.0	0.070	0.055

Notes: N = 99,924 applicants, all of which filed applications to the OHIM from 1996 to 2004 and held a portfolio of ≥ 1 registered trademarks. N = 2,615 for a portfolio size of ≥ 10. N = 580 for a portfolio size of ≥ 25. SD = Standard deviation.

Dividing the cumulative number of Nice classes granted protection by the number of trademarks reveals the average breadth of a portfolio. The mean value is 2.58 Nice classes per trademark. Hardly any differences can be observed for larger portfolios. The average portfolio consists mainly of pure product marks (53.9%). This percentage share is higher for applicants with larger portfolios. On average, the seniority intensity of each portfolio is 0.48. Again, this value increases when larger applicants are considered. For larger portfolios, this indicates a greater share of previously established trademarks. Since the applicant-level is regarded, not only oppositions received are observed but also those lodged against rivals. The opposition intensity with regard to oppositions brought is 0.007 for all applicants and increases considerably when only larger applicants are regarded. Applicants owning larger portfolios more actively monitor the trademark universe and lodge oppositions. The same pattern, but to a smaller extent, can be found for oppositions received.[31] Regarding the country of origin, 19.7% of all applicants come from the US, 15.4% from Germany, and 12.6% from the UK. These proportions shift when only applicants with larger portfolios are considered. Then, the share of non-EU residents rises while the share of companies based in the EU declines. This reflects a home bias for small- and medium-sized EU residents. In contrast to that, non-EU applicants need to be large enough to engage and seek protection in a remote market.

As shown above, application behavior has country-specific influences. Hence, it is interesting to further examine applicants' countries as presented in Table 7. The distribution of trademarks by countries is rather similar. Table 7 suggests, once again, that applicants from the EU make up the lion's share of all applicants and all trademarks although they, on average, have fewer trademarks per applicant. This is likely due to the increased propensity of small- and medium-sized applicants to apply for trademarks in their home market. Drawing on the characteristics of trademarks, I first elaborate on the failure rate of each country. Considerable heterogeneity can be observed ranging from 16.5% (Switzerland) to 38.8% (Canada). Even though a clear-cut pattern is not identifiable, remote countries with respect to Europe seem to exhibit greater difficulty getting their applications registered. The following four characteristics are divided by the number of registered trademarks in order to obtain normalized values: Nice classes, seniorities, oppositions brought, and oppositions received. Regarding Nice classes, the same country-specific pattern seems to prevail with remote countries exhibiting a smaller breadth of trademarks. The pattern for seniorities clearly demonstrates that countries with a long industrial tradition tend to have higher values due to their established (and previously registered) trademarks. An assessment of oppositions reveals a rather interesting pattern. Most economies tend to show a rather

[31] Recall that, in order to lodge oppositions, opponents need to hold an IP right that does not necessarily need to be a CTM. Thus, all oppositions received by CTMs are covered by the OHIM database. However, not all of these oppositions originate from applicants holding CTMs. A substantial share of those oppositions originates from outside the 'universe' of CTM applicants. The number of oppositions brought by CTM applicants recorded in the OHIM database is therefore lower than the number of oppositions received. In other words, this explains why brought and received oppositions do not balance.

low degree of defensive measures as indicated by lodging oppositions against others. In contrast, Swiss and German applicants behave quite aggressively to secure their trademarks. Finally, primarily small EU countries must deal with a high degree of oppositions received whereas remote countries or large EU economies tend to be rarely opposed. To conclude these insights, remarkable heterogeneity between countries exists demonstrating asymmetrical traffic between oppositions received and those lodged. It seems to be less plausible that cultural determinants play a major role. Rather, geographical distance from Europe and diverse characteristics of the applicant populations in these countries seem to matter.

Table 7: Countries of Trademark Applicants

							Per trademark [3]			
									Oppositions	
Country	Applicants	%	Trade-mark	%	TM per applt. [1]	% failed appln. [2]	Nice classes	Senior-ities	Brought	Re-ceived
Austria	1,597	1.6%	3,190	1.4%	1.997	0.288	2.992	0.668	0.013	0.429
Belgium	1,789	1.8%	3,440	1.5%	1.923	0.199	2.614	1.137	0.010	0.359
Canada	1,409	1.4%	2,743	1.2%	1.947	0.388	2.195	0.323	0.011	0.286
China	780	0.8%	1,281	0.6%	1.642	0.244	2.148	0.286	0.010	0.381
Denmark	1,607	1.6%	3,699	1.6%	2.302	0.241	2.532	0.997	0.016	0.384
Finland	1,053	1.1%	2,303	1.0%	2.187	0.213	2.528	0.349	0.012	0.319
France	7,061	7.1%	14,741	6.4%	2.088	0.191	2.878	0.963	0.024	0.286
Germany	15,390	15.4%	37,806	16.5%	2.457	0.215	2.982	0.841	0.070	0.359
Greece	361	0.4%	580	0.3%	1.607	0.238	2.867	0.619	0.002	0.607
Ireland	1,047	1.0%	2,086	0.9%	1.992	0.283	2.713	0.239	0.011	0.357
Italy	9,314	9.3%	18,108	7.9%	1.944	0.174	2.523	0.472	0.008	0.363
Japan	1,582	1.6%	7,120	3.1%	4.501	0.210	2.153	0.896	0.017	0.173
Luxembourg	489	0.5%	1,169	0.5%	2.391	0.269	2.960	0.465	0.011	0.381
Norway	333	0.3%	536	0.2%	1.610	0.231	2.332	0.414	0.009	0.403
Portugal	753	0.8%	1,390	0.6%	1.846	0.266	2.163	0.519	0.020	0.465
Spain	9,344	9.4%	15,907	6.9%	1.702	0.171	2.721	0.771	0.034	0.404
Sweden	2,685	2.7%	5,099	2.2%	1.899	0.236	2.442	0.491	0.014	0.308
Switzerland	1,615	1.6%	5,161	2.2%	3.196	0.165	2.813	1.469	0.078	0.334
Taiwan	1,006	1.0%	1,654	0.7%	1.644	0.227	1.715	0.065	0.006	0.325
The Netherlands	2,562	2.6%	5,899	2.6%	2.302	0.258	2.677	1.210	0.037	0.358
UK	12,601	12.6%	29,037	12.6%	2.304	0.276	2.837	0.671	0.023	0.371
US	19,724	19.7%	55,851	24.3%	2.832	0.305	2.155	0.600	0.026	0.275
Other countries	5,822	5.8%	10,827	4.7%	1.860	0.274	2.192	0.242	0.010	0.409

Notes: N = 229,627 registered trademarks filed with the OHIM from 1996 to 2004 by 99,924 applicants. To determine the countries in which trademarks are located, applicants' country assignments were used. SD = Standard deviation. applt. = applicant. appln. = application.

[1] To compute these values, the number of CTMs was, for each country, divided by the number of applicants.

[2] To compute these values, the number of CTM applications was, for each country, divided by the number of CTMs.

[3] The values in these columns were computed by dividing the number of Nice classes, the number of seniorities, the number of oppositions brought, and the number of oppositions received by the number of CTMs.

3 The Market Value of R&D, Patents, and Trademarks

3.1 Introduction

Firms are organizations that combine a broad range of different assets and resources to develop, manufacture, and sell their products. Besides physical assets such as property, plants and equipment, firms have intangible assets that become increasingly important. Intangible assets include, among others, knowledge assets, customer networks, brands, and reputation. Financial investors assess firms' tangible and intangible assets and form expectations about their future performance. Research has frequently found that knowledge assets such as R&D investments and patents contribute to company values in financial markets (e.g., Blundell *et al.*, 1999; Cockburn and Griliches, 1988; Griliches, 1981; Hall *et al.*, 2005). The economic value of other intangible assets has rarely been studied although other IP rights, including trademarks, are increasingly important for companies. With few exceptions (Bosworth and Rogers, 2001; Greenhalgh and Rogers, 2006a, 2006b), trademark rights were not considered in the discourse of evaluating the economic value of intangible assets. Compared to patents, they are rather invisible in economic research. While patents are regularly and extensively investigated in the field of industrial organization, this is not the case for trademarks although related issues such as product differentiation, product positioning, brands, and advertising have been considered (Cabral, 2000a; Church and Ware, 2006; Tirole, 2003). Graham and Somaya (2006) and Mendonça *et al.* (2004) also note that the paucity of research on trademarks is surprising given their importance for companies to protect their brands.

Trademarks are important to companies because they enable consumers to identify the products of one company and to distinguish them from those of competing businesses (Besen and Raskind, 1991; Landes and Posner, 1987). They also provide incentives for firms to offer products of a consistent and reliable quality (Cabral, 2000b; Economides, 1988; Landes and Posner, 1987). Trademark law has three main requirements for establishing a valid trademark right (European Council, 1993, Art. 4, and Art. 7). First, a trademark can be any sign that is capable of being represented graphically. Naturally, words and graphical signs (e.g., logos or symbols) fulfill this condition. Three-dimensional shapes, colors, and even sounds are, in principle, also registrable as long as they can be graphically represented (Mendonça *et al.*, 2004). The second requirement is distinctiveness, which means that customers are able to recognize a sign as being a trademark and distinguish it from other trademarks within an appropriately defined product category (Besen and Raskind, 1991; Landes and Posner, 1987). Thus, the concept of distinctiveness ensures that a sign, for which protection is sought, is neither identical nor too similar to other already existing IP rights (Besen and Raskind, 1991; European Council, 1993, Art. 8). The third requirement concerns absolute grounds for refusal and, for example, guarantees that generic words or signs cannot be registered (European Council, 1993, Art. 7).[32] Trademarks can be viewed as direct commercial links between a company and its actual and prospective customers (Economides, 1988; Malmberg, 2005; Phillips, 2003). A prominent example is *Intel*. With its slogan *Intel Inside*, it built a strong and direct connection to its end customers thereby bridging downstream distributors (Afuah, 1999).

The rights conferred by valid trademark registrations endow owners with legal instruments to preserve their trademarks' exclusivity (European Council, 1993, Art. 9). These rights primarily allow a trademark holder to prevent others from counterfeiting or taking unfair advantage of the trademark. Moreover, to maintain the distinctiveness of an existing trademark, owners can file oppositions if they find that a third party's trademark application is too similar or even identical to their own (European Council, 1993, Art. 8, and Art. 42; Phillips, 2003; von Graevenitz, 2007). A successful opposition leads to the rejection of a hostile trademark application. Trademark rights thus allow their holders to protect their assets such as brand names and reputation against impairment. In sum, trademark rights allow their owners to maintain a commercial link to consumers that is "free from interference" (Phillips, 2003, p. 25) by the detrimental activities of competitors. Trademarks and brands are highly intertwined (Mendonça *et al.*, 2004). The former represents the legal basis upon which the latter builds.[33] Investments in brands, in particular advertising, would be useless if trademark rights did not prevent rivals from unfairly appropriating the value of an owned trademark, for example, through counterfeiting or imitation. Consequently, trademark rights can be viewed as legal anchors of brands. The importance of trademarks is also documented

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32 Thus, the word *Apple* does not qualify for registration as applied to food because it is a generic term with regard to this product category. Yet, it is eligible for protection when used for computers.

33 Within the field of business administration, a large body of literature discusses how consumers perceive brands and how companies successfully build brands. However, this area of research has not regarded the importance of trademark rights for acquired assets such as brands or reputation.

in the immense number of trademark applications in Europe.[34] At the end of 2007, over 640,000 CTM applications have been filed with the OHIM. Of these applications, approximately 420,000 became registered as CTMs (OHIM, 2007).

The objective of this chapter is to assess the economic value of trademarks and knowledge assets. More specifically, I explore the relationship between firms' valuations in the stock market and their assets (Tobin's *q*). Depending on their strategy, firms determine the amount of funds to invest in knowledge or brand assets. While knowledge assets measure innovation, trademarks transmit messages to the consuming public and facilitate product choice (Economides, 1988). Financial markets assess the prospective returns that arise from these investments. To measure knowledge assets, R&D investments and patents are frequently used in market value equations. The use of trademarks in market value equations, however, is rather new. A further aim of this work is to scrutinize the economic relevance of several indicators which are expected to reflect trademark value. These indicators are obtained from publicly available trademark data and can thus be widely applied. They are: (i) Nice classes informing us about the breadth of trademarks, (ii) seniorities reflecting the familiarity of the consuming public with trademarks, (iii) oppositions brought against rivals indicating the intensity with which a company protects its presumably valuable brand assets, and (iv) oppositions received from rivals reflecting third parties' honoring of the potential value of owned trademarks. According to these indicators, the value of trademarks is greatly dispersed. Although they allow us to characterize trademarks and their portfolios in more detail, their association with firm value, in order to demonstrate their economic relevance, has not yet been shown.

The following two main research questions are addressed. First, are trademarks economically valued in stock markets and do trademarks, compared to knowledge assets, add further value in explaining company values? Second, which indicators of trademark value can, similarly to patent value indicators, be constructed from trademark data and are these indicators informative about trademark value? To address these questions, the market value approach, initially presented by Griliches (1981), is further developed to incorporate trademarks and their value indicators. The value indicators were initially presented by von Graevenitz (2007), who used them to determine trademark opposition outcomes. To corroborate the applicability of these indicators to

[34] The CTM is valid in all member states of the EU. The CTM system was established by the Regulation No. 40/94 of the European Council (1993). According to this act, the OHIM which administers the CTM system commenced trademark examination operations in 1996.

trademarks, reference is made to the patent literature since research in this area has already led to the development of several patent value indicators drawn from publicly available patent data. I compile a comprehensive dataset including the world's largest publicly traded corporations. In addition to annual accounting and financial data, firm-level IP portfolios are constructed comprising both trademarks and patents. The IP rights considered in these portfolios are European Patents issued by the EPO and CTMs granted by the OHIM. European Patents and CTMs roughly cover the same geographical area. Trademark data, in particular CTMs, have very rarely been employed in the analysis of company valuations, compared to accounting, financial, and patent data. Regarding patents, citations were used to account for the greatly dispersed patent value (Harhoff *et al.*, 1999). The dataset employed to estimate the market value equation has the structure of an unbalanced panel, and it comprises 6,757 observations on 1,216 companies for the years 1996 through 2002.

The results indicate that both knowledge assets and trademarks are economically valued in the stock market. Both measures of knowledge assets, investments in R&D and patents, were positively associated with Tobin's q. However, it was found that investors do not value merely counted patents but assess their inherent value. The contribution of trademarks to firms' market values was very robust and yielded a higher explanatory power compared to the measures of knowledge assets. Investors clearly assign a higher value to companies with larger trademark portfolios. Trademark value indicators were found to add further value as demonstrated by the following observations. First, more diversified companies as indicated by the breadth of trademarks seem to experience a discount in the financial market. Second, trademarks are of higher value if they are well established as indicated by seniority claims. Finally, companies that defend their trademark portfolio more vigorously are more highly valued. This renders trademark oppositions economically relevant and shows that companies, which lodge many oppositions against others, seek to protect the value of their brand assets. Interestingly, knowledge assets and trademarks carry some degree of common information. This is attributable to companies' engagement in new product development since new products require knowledge assets for developing them and trademarks for selling them. The results are claimed to be representative of large stock exchange-listed corporations. As an IP right, trademarks are registrable for the whole product and service space. This is in contrast to previous studies on patents since the use of patents is concentrated in technology-related industries.

The remainder of this chapter is divided into four sections. Section 3.2 presents the market value approach. Drawing on previous studies on the market valuation of knowledge assets and trademarks, it describes the method used to estimate the economic value of knowledge assets and trademarks using financial data. Section 3.3 presents the data and describes the variables while Section 3.4 reports the results of estimating the market value equation. Finally, Section 3.5 provides a conclusion that also addresses the limitations of this chapter and indicates avenues for future research.

3.2 Trademarks and the Market Value Approach

This section describes the market value approach (Section 3.2.1) and discusses how trademarks are accommodated in the market value equation (Section 3.2.2). Four indicators are presented to account for the great dispersion in trademark value (Section 3.2.3). To incorporate those indicators in the market value equation, I follow an approach based on Hall *et al.* (2005), who include patent citations in the market value equation to account for patent value (Section 3.2.4). Finally, I highlight issues related to the estimation of the model (Section 3.2.5).

3.2.1 The Market Value Approach

The market value approach, which combines accounting data of firms with their valuation in financial markets (Lindenberg and Ross, 1981; Montgomery and Wernerfelt, 1988), has frequently been employed to assess returns to innovation and the economic value of intangible assets.[35] According to this approach, the value of a company encompasses tangible and intangible assets. In financial markets, investors estimate a company's value according to the prospective returns that they expect from its assets. Expectations about the future performance of a company are embodied in its stock price. If stock markets are efficient, the company value equals the sum of discounted future cash flows (Fama, 1970). The market value can therefore be viewed as a forward-looking measure of firm performance (Hall, 2000). Since the market value approach rests on the assumption that companies are bundles of assets, this approach is comparable to hedonic price models. Those models seek to disentangle the price of a good and measure the contribution of each single characteristic to that good's price (Hall *et al.*, 2007). Correspondingly, the market value approach assumes that the price of a company, determined in the financial market, is a function of the assets of the

[35] An analytical evaluation of econometric approaches to assess the economic value of R&D is presented by Hall (2007).

company. These assets are either tangible or intangible and include inventory, plants and equipment, customer relationships, reputation, brands, and knowledge assets (Hall *et al.*, 2007). Following the initial work of Griliches (1981), the typical linear market value model assumes that firms' assets enter the market value equation additively:

$$V_{it}(A_{it}, K_{it}) = q_{it}(A_{it} + \gamma K_{it})^{\sigma}, \tag{1}$$

with

$$q_{it} = \exp(y_t + c_k + m_l + u_{it}). \tag{2}$$

The value of company i at time t is given by V_{it}. Physical assets are represented by A and knowledge assets by K. Both categories of assets are summed up, implying that a firm is equal to the sum of its components. The current valuation coefficient, q_{it}, of the company's assets at a specific time captures factors that affect the valuation multiplicatively (Hirsch and Seaks, 1993). Such factors may include market structures or differential risks (Griliches, 1981). q_{it} includes an individual disturbance, u_{it}, and variables accounting for valuation effects regarding time t, country k, and industry l. These overall valuation effects are shown by y_t, c_k, and m_l, respectively.

σ measures returns to scale and is unity if the value function is homogeneous of degree one, indicating constant returns to scale (Pemberton and Rau, 2001, pp. 263-265). Because σ relates to a sum, its size may also provide insight into the relationship between the addends A and γK. Economies of scale exist if σ exceeds 1. This may indicate that the addends are complements.

The marginal value γ reflects the contribution to the company's value when one additional unit is spent on knowledge assets. When $\sigma = 1$, γ is the relative shadow value of knowledge assets to physical assets (Hall, 1993c; Hall and Oriani, 2006). Accordingly, the product $q_{it}\gamma$ is the absolute shadow value reflecting the expectations of investors. Following Hall and Oriani (2006), I do not allow γ to vary over time although this would be more accurate (Hall, 2000; Toivanen *et al.*, 2002). The shadow value is not to be interpreted as a structural parameter; it measures neither the supply of nor the demand for knowledge assets. Instead, marginal values are equilibrium outcomes in the financial market, resulting from the interaction between companies' investment activities and investors' evaluations of these (Hall, 2000; Hall and Oriani, 2006).

Knowledge assets, *K*, can be represented by R&D investments (Hall, 1993b, 1993c; Hall and Oriani, 2006; Jaffe, 1986; Johnson and Pazderka, 1993) or patents (Blundell *et al.*, 1999). Several studies incorporated both R&D and patents in the market value equation (Bloom and van Reenen, 2002; Connolly and Hirschey, 1988; Griliches, 1981; Griliches *et al.*, 1991; Hall *et al.*, 2005; Megna and Klock, 1993; Toivanen *et al.*, 2002). Importantly, mere patent counts have been found to be less informative than citation-weighted patent stocks, which account for the great dispersion in patent value (Hall *et al.*, 2005).

Note that all assets are stock variables (as opposed to flow variables).[36] Financial markets price a company according to the future cash flows induced by the various assets of the company. Past investments have built the knowledge base with which the company develops its products today. Of course, knowledge assets depreciate over time, but these past investments influence investors' appraisal of the future development of the company and, therefore, the valuation of a firm. Accordingly, stock variables were computed in this study. This approach is different from that of Greenhalgh and Rogers (2006a), who employ flow variables for R&D and implicitly assume a depreciation rate of 100%.

3.2.2 Including Trademarks in the Market Value Equation

The accommodation of trademarks in the market value equation is rather straightforward although, in principle, two possibilities exist for incorporating trademarks. First, trademarks may be treated as an asset class that is symmetrical to knowledge assets. An additional additive term comprising trademark stocks is then included in the market value equation. This method is applied in other studies (Bosworth and Rogers, 2001; Greenhalgh and Rogers, 2006a, 2006b). Second, trademarks may be incorporated in the multiplicative factor q_{it} since they may affect or influence market structures. It has been pointed out that the characteristics of a company's market position should be accounted for in this multiplicative factor. Griliches (1981) considered a company's monopoly position as well as its risk profile structures to be incorporated in q_{it}. Hirsch and Seaks (1993) highlighted measures of market structures. Trademarks protect companies' assets from erosion and allow their owners to defend their brands

[36] A flow variable captures the annual inflow (e.g., annual flows of trademarks, patents, or R&D expenditures) to a stock. Conversely, a stock variable measured in period t aggregates all annual inflows up to t. If, for example, a company has a portfolio of 100 trademarks in $t-1$ (stock variable) and files 10 trademarks in t (flow variable), the stock in t consists of 110 trademarks. The stock in $t-1$ might be depreciated to account for obsolescence (Hall, 2007).

against interference by rivals (Phillips, 2003). This permits companies to maintain and foster their market positions (Besen and Raskind, 1991; Economides, 1988; Rujas, 1999). It can be argued that trademarks are instruments that enable leveraging of other assets. As trademarks establish commercial links between a company and its consumers, they may freeze market structures, thus raising barriers to new entrants through consumer loyalty (Demsetz, 1982).

However, I follow the first possibility for the following reasons and treat trademarks symmetrically to other assets. Adding trademark stocks separately and symmetrically to knowledge assets follows the approach of Hall and Oriani (2006), who include "other intangible assets" (p. 975) in addition to physical assets and knowledge assets. Hall *et al.* (2007) state that the assets owned by a firm also include customer networks, brand names, and reputation. They assume, moreover, that different types of assets enter the market value equation symmetrically and additively. According to this practice, advertising expenditures (Connolly and Hirschey, 1988; Hall, 1993c; Hirschey and Weygandt, 1985; Villalonga, 2004) and trademarks (Bosworth and Rogers, 2001; Greenhalgh and Rogers, 2006a, 2006b) have been included in market value equations. Trademark rights can be viewed as the foundation on which a company's brand or its reputation can be built (Phillips, 2003). The term 'brand equity' (Aaker, 1991) clearly shows that brands, and trademarks as their legal basis, are one asset class among others. Moreover, if patents are used as a measure for K and, thus, are included as an additive term, both mechanisms to protect IP are treated in an analogous way to knowledge assets. Therefore, the market value equation

$$V_{it}(A_{it}, K_{it}, M_{it}) = q_{it}(A_{it} + \gamma_K K_{it} + \gamma_M M_{it})^{\sigma} \tag{3}$$

incorporates trademark portfolios, M, as an additional additive term. The symmetry with which the asset classes are treated assumes that a company is principally able to choose between investments in these types of assets. The shadow value of trademarks relative to physical assets is given by γ_M. Taking logarithms of both sides and subtracting the logarithm of A results in

$$\log\frac{V_{it}}{A_{it}} = \log q_{it} + (\sigma - 1)\log A_{it} + \sigma \log\left(1 + \gamma_K \frac{K_{it}}{A_{it}} + \gamma_M \frac{M_{it}}{A_{it}}\right). \tag{4}$$

The fraction on the left side of Equation 4 represents Tobin's q, the ratio of the market value of a company to its physical value. The current market valuation coefficient, q_{it}, is given by Equation 2.

3.2.3 Indicators of Trademark Value

The value of patents was found to be highly skewed (Harhoff *et al.*, 1999; Harhoff *et al.*, 2003b). Several indicators informing about their value can be derived from patent registration files. Research has shown that such indicators are correlated with more direct measures of patent value (Harhoff *et al.*, 1999; Harhoff *et al.*, 2003a). Trademarks are also subject to a great dispersion in their value (see Barth *et al.*, 1998 concerning brand values). The value of a trademark is rooted in its ability to positively influence consumers and their purchasing decisions (Economides, 1988). This capability of a trademark is also known as goodwill (Phillips, 2003; Smith, 1997).[37] The development of indicators reflecting trademark value rests on the assumption that more valuable trademarks are treated differently by their owners and their rivals than less valuable trademarks. Given this assumption, these differences should also be observable in the publicly available registration files of trademark offices. The indicators that inform about trademark value include the breadth of trademarks, claimed

Table 8: Value Indicators of Trademarks

Measure	Rationale regarding trademarks	Related concept for patents	References within the area of patents	Possible levels of analysis
Nice classes of a trademark	– Breadth regarding goods and services covered	– Scope of technological classes – Claims	Lerner (1994); Harhoff and Hall (2003)	Firm, trademark
Seniorities claimed	– Familiarity and diffusion due to previously existing trademarks – Reflecting potential awareness	– Geographical coverage as measured by the size of patent families – Targeted markets	Putnam (1996)	Firm, trademark
Oppositions brought by an applicant	– Monitoring activity and capability of perceiving threats – Protection of own assets, degree of aggressiveness and willingness to damage others	– Monitoring activity and capability of perceiving threats – Protection of own assets, degree of aggressiveness and willingness to damage others	Harhoff *et al.* (2003a)	Firm
Oppositions received by a trademark application	– Being recognized and monitored – Being a potential threat to competitors or other firms – Owning potentially valuable assets	– Being recognized and monitored – Being a potential threat to competitors or other firms – Owning potentially valuable assets	Harhoff *et al.* (2003a)	Firm, trademark

[37] This meaning is different from the meaning of 'goodwill' as an accounting item occurring in the case of an acquisition. As an accounting item, goodwill is the difference between the book value of an acquired company and the company value paid by the buyer.

seniorities, oppositions lodged against others, and oppositions received from rivals. With the exception of von Graevenitz (2007), who pointed out that these indicators are relevant for opposition cases, they were not studied in depth yet. The rationale for each measure is outlined below, and Table 8 summarizes these insights. Where possible, a comparison to patents is drawn because value indicators of patents have been intensively discussed in the literature.

The breadth of a trademark is captured by the number of goods and service classes for which it is registered. When filing an application, it is possible to seek protection for several goods and service classes. Assessing the signs trademark rights protect reveals that those trademarks associated with few classes tend to protect single products or narrow product lines, for example *Microsoft Office 2000* or *iPod*. By contrast, trademarks like *Daimler* or *PlayStation* are awarded to many classes and seem to protect wider product lines or so-called umbrella brands (Cabral, 2000b; Erdem, 1998).[38] The classes are set out by the Nice Classification and span 34 goods and 11 service classes (WIPO, 2006).[39] This scheme is rather crude compared to the International Patent Classification (IPC), which provides a detailed scheme to classify technologies (Schmoch, 2003). Comparable to the technological scope of patents indicated by IPC classes (Lerner, 1994), Nice classes represent the market scope of a trademark. The common element of IPC and Nice classes concerns the classification in the technology or market space, but an important distinction between IPC and Nice classes remains. Nice classes also span the scope of legal protection while IPC classes perform no such function. The more Nice classes for which a trademark is registered, the broader the scope of legal protection. With patents, the scope of legal protection is defined by their claims. Therefore, the claims of a patent and the Nice classes of a trademark both determine the scope of legal protection. Accordingly, application fees increase as more claims (Harhoff and Hall, 2003) or more Nice classes (Mendonça *et al.*, 2004) are specified. Due to the scope of protection indicated by the number of Nice classes, it can be expected that a trademark with a larger breadth reflects a higher value.

Consumers' awareness of a trademark is a key driver of its value (Aaker, 1991), and their familiarity with a trademark or its diffusion in the market is indicated by the seniorities carried by a CTM. Seniorities account for the number of previous registra-

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[38] A brand can be said to be an umbrella brand if it spans several products (Erdem, 1998; Wernerfelt, 1988).

[39] Note that, due to revisions of the Nice Classification, only 42 classes could be considered until the end of 2001. Thereafter, 45 classes were considered (also discussed in Section 2.6.1).

tions in other jurisdictions. A seniority of an earlier national trademark can be claimed if the CTM applied for is identical to or contains the earlier trademark (European Council, 1993, Art. 34). This mechanism ensures that the right of an earlier national trademark, if lapsed or surrendered by the owner, is continued through a subsequent CTM. A CTM claiming several seniorities refers to a bundle of previous registrations. Consequently, more consumers have already been confronted with that trademark, resulting in a higher familiarity and higher potential awareness. Thus, trademarks with more seniorities are likely to be of higher value than trademarks with fewer seniorities. Greenhalgh and Rogers (2006a) have found a consistently higher economic value for CTMs than for national trademarks held by UK-based owners. With patents, a similar indicator is the size of a patent family, which reflects the geographical coverage of a patented invention (Putnam, 1996). Both seniorities and the size of patent families indicate the geographical scope of protection.[40] However, since seniorities capture only earlier trademark rights, this value indicator is biased when applicants file trademark applications directly with the OHIM and do not register national trademark rights, for which seniorities would be claimed when they later apply for a CTM.

Oppositions have been shown to indicate the value of patents (Harhoff and Reitzig, 2004; Harhoff *et al.*, 2003a). Due to similar legal processes, the rationale of oppositions as indicators of value also applies to trademarks. A company opposes another's trademark if it seeks to stop the potential IP right from being granted. At the end of 2007, 125,313 oppositions were filed with the OHIM (OHIM, 2007). With trademarks, the legal ground on which a company lodges an opposition against a rival is the concept of distinctiveness (European Council, 1993, Art. 8). A trademark is registrable only if consumers can distinguish it from other existing trademarks (European Council, 1993, Art. 4, and Art. 7; Landes and Posner, 1987). This principle ensures that new trademark applications are neither identical nor too similar to earlier trademark rights (Besen and Raskind, 1991). The yardstick to determine the degree of distinctiveness is the likelihood of consumers' confusion (Phillips, 2003). Accordingly, the proprietor of a registered trademark has the ability to oppose another trademark if he thinks that consumers might be confused by it (European Council, 1993, Art. 42).[41] If successfully opposed, this attacked trademark application is rejected. Oppositions involve

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[40] Note that the number of seniorities does not need to correspond to the number of countries. The CTM registration of *Shell*, for example, claims 306 seniorities, of which 61 refer to the UK and 48 refer to Portugal. This is because a seniority may be claimed not only if the CTM application refers to identical previous rights but also if it merely contains a sign which is already protected by an earlier trademark right.

[41] An opposition can be lodged within three months following the publication of a CTM application (European Council, 1993, Art. 42).

several categories of costs. Time and money must be spent to monitor competitors, perceive potential threats, and prepare and file oppositions. Furthermore, the attacked party can raise the opponent's costs if it requests a proof of use, which would require the opponent to present adequate evidence that the earlier trademark right was indeed used in the course of trade (European Council, 1993, Art. 43). Despite these costs, the opponent usually files an opposition if he expects substantial damages from the eventually registered application (von Graevenitz, 2007). Such damages involve the potentially unfair appropriation of a trademark's value or the possibility of competitors obtaining new trademarks for branding and market entry. Oppositions allow a company to protect its assets and neutralize or reduce the anticipated damage. More valuable trademarks will be protected more vigorously. Filing oppositions might also enable a company to weaken rivals' branding aspirations or delay them. The value of a trademark portfolio brought to bear against rivals might even increase if a company is able to build a reputation for toughness, influencing both behavior in and outcomes of future opposition cases (von Graevenitz, 2007). Thus, it is hypothesized that a company's opposition filing activity will reflect the value of the underlying trademarks.

In addition to oppositions lodged against others, the number of oppositions received from rivals also reflects a trademark's potential value. Once again, the opposition activities of rivals seek to stall trademark applications which are potentially dangerous. The attack against a trademark application can be viewed as a strong endorsement or an acknowledgment of a trademark's value (Phillips, 2003). Those assets of potentially high value lead rivals to oppose them. Hence, it is expected that, *ceteris paribus*, the more oppositions a trademark attracts, the higher its potential value.

3.2.4 Accounting for Trademark Value in the Market Value Equation

Having already presented indicators of trademark value and discussed how trademarks enter the market value equation, I now describe the approach used to account for the dispersion of trademark value in the market value equation. The method used to include the measures of trademark value in the market equation is similar to that employed by Hall *et al.* (2005), who use citations as an indicator of patent value. They assume that patents will induce citations at a certain rate. This rate reflects the average value of patents and is embodied in the market expectations, but citations carry additional informational value if the rate at which patents turn into citations is above average or rises unexpectedly. This idea can be transferred to trademarks. Trademarks will invoke oppositions by rivals at a certain rate. The market assumes that a given number of trademarks will, following an average expectation, induce a certain number of oppositions. Trademarks of higher values will attract more oppositions; thus, the rate at which these trademarks turn into received oppositions will be higher. Trademark portfolios can be characterized by this rate, which is termed opposition intensity.

Similar to the number of oppositions received from rivals, the other three value indicators can be applied in analogous ways. With a given number of trademarks, a company files oppositions against others at a certain rate. Thus, a higher rate of oppositions brought can, *ceteris paribus*, be explained by more valuable assets. Intensities may also be calculated for seniorities and the breadth of trademarks. Accordingly, the trademark portfolio is, for each value indicator j, characterized by the ratio of the indicator stock, W_j, to the trademark stock, M. Based on Equation 4, these intensities are incorporated in the market value equation as shown by:

$$\log \frac{V_{it}}{A_{it}} = \log q_{it} + (\sigma - 1)\log A_{it} + \sigma \log\left(1 + \gamma_K \frac{K_{it}}{A_{it}} + \gamma_M \frac{M_{it}}{A_{it}} + \xi_j \frac{W_{jit}}{M_{it}}\right). \qquad (5)$$

3.2.5 Estimation Method

Comparable to Hall *et al.* (2007), the data obtained in this study have the format of an unbalanced panel. I follow the practice of not controlling for unobserved firm-specific components for two reasons. First, the objective of this study is to analyze the economic value of trademarks and knowledge assets *across* a wide range of different companies, leading to a pooled regression framework. Second, physical assets, knowledge assets and trademarks adjust rather slowly from year to year. Including firm-specific fixed effects would lead to a rather low degree of variance in the data. The period of observation applied here is too short to observe major changes in assets within companies, but, to account for time-dependent overall effects in financial markets, a full set of year dummies is included following other studies (Blundell *et al.*, 1999; Griliches, 1981). Furthermore, full sets of country and industry dummies capture regional and industry-specific variations in valuations (Hall *et al.*, 2007).

To estimate the market value equation, NLLS regression techniques will be employed (Hall *et al.*, 2005; Hall *et al.*, 2007). Early research in this area has approximated $\log(1 + x)$ by x, allowing an estimation using ordinary least squares (OLS) (Cockburn and Griliches, 1988; Griliches, 1981; Jaffe, 1986). This approximation, however, is not accurate if x is large. As Hall *et al.* (2007) note, this approximation becomes inappropriate with an increasing ratio of knowledge assets to physical assets. They suggest that NLLS is the appropriate estimation method in this case because it allows for the estimation of non-linear functions as it is the case with the market value equation. Due to the non-linear functional form, however, interpretation of the coefficients is not straightforward for those embedded in non-linear terms. Moreover, the regressors carry various units (e.g., Euros, patents, trademarks). To facilitate comparisons and to ease the interpretation of these coefficients, I compute the elasticities for each of the key regressors with respect to Tobin's q, also accounting for non-linearity.

3.3 Data Sources, Operationalization and Descriptive Statistics

The model developed in the previous section is estimated with a comprehensive dataset that includes accounting, financial market, trademark, and patent data. Trademarks and patents were consolidated at the corporate level to build firm-level IP portfolios. This section describes the various data sources and how they were connected (Section 3.3.1). It also discusses the variables that enter the empirical model (Section 3.3.2) and presents descriptive statistics (Section 3.3.3).

3.3.1 Data Source and Sample

Data from three different sources were used. Accounting and financial market data were obtained from the Compustat database.[42] Trademark data were taken from the CTM register provided by the OHIM. For patent data, the worldwide patent database PATSTAT was used.[43] Patent citation data were taken from the Patent Citation Project of Dietmar Harhoff.

Since estimating the market value equation requires knowledge of the market values of companies, only publicly traded companies could be considered. The Reuters and the Compustat databases were used to identify the world's largest stock exchange-listed companies as measured by total revenues.[44] I started with all publicly traded companies having revenues of at least 400 million Euros in their last financial statement. This selection criterion yielded a total of 4,085 companies. Based upon the goal of providing representative evidence for large players listed at stock exchanges, no restrictions

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[42] More specifically, I used the GlobalVantage database, which is the license covering international data within the Compustat database provided by *Standard & Poor's*.

[43] The version of October 2007 was employed. The EPO Worldwide Patent Statistical Database (PATSTAT) is available under license from the OECD-EPO Task Force on Patent Statistics.

[44] As a financial database, Reuters was used to double-check the set of publicly traded companies and the accuracy of company names. The names of companies are required to connect trademark and patent data with accounting and financial data at the firm-level (see appendix).

regarding the industrial sector were imposed. Compustat provided accounting and financial market data from 1990 to 2006. More specifically, companies' total assets, total debt, R&D expenditures, and market capitalization at the end of each year were obtained. The Compustat data was manually checked for several companies. It was confirmed that these data correspond to the published annual reports. Historical currency rates were used to produce consistent Euro values. These values have been deflated to real 2000 prices using Ameco, an annual macro-economic database provided by the European Commission.[45]

CTMs were extracted from the OHIM database and European Patents from PATSTAT in order to build firm-level IP portfolios. The OHIM database has been described in Section 2.6. Recall that this database was recorded at the end of 2004. Naturally, not all CTM applications filed until that date have already been fully processed. As the share of applications still being in process increases with later cohorts, the number of registered CTMs, in particular for the 2003 and 2004 cohorts, drastically decreases. Since this chapter focuses on granted IP rights, the trademark data were truncated so that only those CTMs were used that were filed before the end of 2002 (see Section 2.6.1).

For the years 1996 through 2002, patents and trademarks were consolidated on the corporate level.[46] The process of matching applicants to corporate entities is outlined in the appendix. For 2,021 companies, neither CTMs nor European Patents could be assigned. Trademarks or patents were matched to 2,064 companies, representing 11,258 annual observations. Since the main interest of this chapter is the economic valuation of trademarks, those companies showing no trademark activity were excluded, leaving 1,297 companies with 8,144 observations. Observations containing missing values were also excluded.[47] This trimming reduced the data to 1,232 companies (7,081 observations). Finally, observations with extreme outliers were excluded.[48] The final dataset consisted of 6,757 observations for 1,216 publicly traded firms. It is

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[45] Website: http://ec.europa.eu/economy_finance/db_indicators/db_indicators8646_en.htm (accessed on February 13, 2008).

[46] Recall that the OHIM commenced its operations in 1996 so that no CTMs could be filed previous to that year.

[47] The dependent variable Tobin's *q* could not be computed for 1,063 observations because at least one of its components was missing (total assets, total debt or market capitalization).

[48] Like OLS, NLLS also shows strong sensitivity to outliers. As a rule for identifying outliers, the 1st and 99th percentiles were computed for the following three measures: Tobin's q, trademark stock / assets, and R&D stock / assets. Observations were deleted if one of the variables was outside the boundaries given by its percentiles. 324 observations were affected.

important to note that a substantial share of observations with zero CTMs remained in the data since some companies applied for CTMs in the later part of the observation period (i.e., not during the first year).[49]

3.3.2 Variables

This section presents the variables that enter the empirical model. First, the dependent variable, Tobin's q, is described. Next, the computation of knowledge assets and trademark stocks is explained.

3.3.2.1 Tobin's *q*

The dependent variable that enters into the empirical model is the natural logarithm of Tobin's q, defined as the ratio of a company's market value, V, to the book value of its assets, A (Greenhalgh and Rogers, 2006a; Hall and Oriani, 2006; Hall *et al.*, 2007). The book value of the assets represents the total value of assets reported on the balance sheet.[50] The market value of a company is defined as the sum of the market capitalization and the market value of its debt. The former is calculated as the stock price multiplied by the number of outstanding shares at the end of each year.[51] Regarding the latter, difficulties arise from observing the market value of a firm's debt. As Hall and Oriani (2006) point out, corporate finance scholars have developed sophisticated approaches to compute accurate measures for Tobin's q, for example, by relying on price multipliers drawn from the corporate bond market (Perfect and Wiles, 1994). However, greater precision can be gained only at the expense of a reduction in sample size (DaDalt *et al.*, 2003). Thus, I followed other studies that have dealt with this issue (Blundell *et al.*, 1992; Blundell *et al.*, 1999) and calculated the total market value of a company "by simply adding the nominal value of outstanding debt to the market capitalization" (Hall and Oriani, 2006, p. 982). As outstanding debt, the sum of total long term debt and debt in current liabilities was used.[52]

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[49] 1,065 observations (171 companies) started to file CTM applications not in the first year of observation but later in the period 1996 through 2002. These observations were not dropped to include the full course of those companies eventually registering CTMs later in the observation period.

[50] The corresponding Compustat item is *AT*.

[51] The Compustat item *MKVAL* is the product of the number of outstanding shares (*CSHO*) and the closing price of each period (*PRCCM*).

[52] The corresponding Compustat item is *DT*. Then, in terms of Compustat items, the Tobin's q is computed as $(MKVAL + DT) / AT$, which is equal to $(PRCCM \cdot CSHO + DT) / AT$.

3.3.2.2 Knowledge Assets

Knowledge assets cannot be directly obtained from accounting data or other sources. Thus, to operationalize knowledge assets, two possibilities exist: investments in R&D and patent data.

Investments in R&D are normally not capitalized in the balance sheets of companies (Ross, 1983). Instead, annual R&D expenditures are recorded in annual income statements as expenses when they occur. To approximate knowledge assets, R&D expenditures have to be capitalized. The history of R&D expenditures of each firm was used to compute R&D stocks. Precisely, the so-called declining balance formula with a constant depreciation rate, δ, is regularly employed, relying on present and past R&D flows (e.g., Hall and Oriani, 2006; Hall *et al.*, 2005; Hall *et al.*, 2007).[53,54] Following other work, a usual depreciation rate of 15% was used to reflect obsolescence of investments in R&D (Hall, 2007):

$$RD_t^{stock} = RD_t^{flow} + (1-\delta)RD_{t-1}^{stock}\,. \qquad (6)$$

To compute the starting R&D stock at the first available observation year of R&D spending, Equation 7 was used with a constant annual R&D growth rate, g, of 8% (Hall and Oriani, 2006; Hall *et al.*, 2007). This assumes that R&D expenditures have been growing at a constant annual rate prior to the observed history:

$$RD_0^{stock} = \frac{1}{\delta + g} RD_0^{flow}\,. \qquad (7)$$

The availability of R&D expenditures raised the following issue. Disclosure of annual R&D expenditures is not compulsory in all countries (Hall and Oriani, 2006). Thus, companies may choose to disclose their R&D spending.[55] Opportunistic behavior by companies renders the decision to report this information endogenous (Toivanen *et al.*, 2002). The consequence might be a potential source of sample selection bias (Belcher, 1996). In addition, for a group of companies, only interrupted histories of annual R&D spending could be established. As described above, the computation of R&D stocks requires full and uninterrupted histories of R&D flows. Those companies that show fragmentary R&D histories or no R&D spending at all were, as in earlier studies (e.g.,

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53 R&D flows equal R&D expenditures. They are drawn from companies' annual income statements and captured by the Compustat item *XRD*.

54 For details regarding the declining balance formula see Hall (1990).

55 Naturally, the absence of R&D data might also be due to the fact that many business models might not require any R&D at all. A separation of these companies from those having chosen not to publish R&D expenditures was not possible.

Hall *et al.*, 2007), treated with a dummy variable. This approach is further substantiated by Hall and Oriani (2006), who found that no sample selection bias was induced by the choice of firms to not disclose their R&D expenditures. As will be revealed later, this dummy shows no significance when estimating the market value equation.

Knowledge assets can also be operationalized by patent stocks, which were calculated in the same way as R&D stocks:

$$P_t^{stock} = P_t^{flow} + (1-\delta)P_{t-1}^{stock}. \quad (8)$$

Once again, a depreciation rate of 15% was used. The annual influx of patents to firm-level patent portfolios was determined according to the filing year of each patent's first priority application.[56] It was not necessary to compute initial stocks since the first year used in the regressions was 1996 and the patent data began in 1978 when the EPO commenced its patent examination operations. Due to the declining balance formula, the effects of approximated initial stocks are negligible (Hall *et al.*, 2007).

The distribution of patent value is highly skewed (Harhoff *et al.*, 1999; Harhoff *et al.*, 2003b). Pure patent counts are less informative compared to measures that account for patent quality (Trajtenberg, 1990). Indicators such as forward citations, patent oppositions, and the size of patent families reflect different dimensions of patent value (Harhoff *et al.*, 2003a; Harhoff and Reitzig, 2004; Putnam, 1996; Trajtenberg, 1990). Although various indicators reflect the value of patents, this study uses citations to approximate the patent value. This builds upon previous research that connected patent citations to the market value of firms (Bloom and van Reenen, 2002; Hall *et al.*, 2005; Hall *et al.*, 2007). After the publication of its search report, a patent may be referenced by subsequent patent documents. These references collected by a patent are called forward citations. In this study, citations of a patent were considered if they arrived within a three-year period after the search report has been published. Within this window, patents receive a substantial share of their lifetime citations (Marco, 2007). To compute value-adjusted patent stocks, each patent of the annual patent flow that

[56] The earliest priority application is the first time a patent application of the underlying invention appears in worldwide patent registers. It might happen that an invention is first patented in the US and later passed on to the EPO to gain protection for European countries. Here, the priority application is the filing in the US while the European filing is a 'derived' one. Together, those patents referring to the same priority application make up a bundle of patents, also called a patent family. The priority filing date of an application has been used for two reasons. First, this date is the earliest recorded date of a patented invention and, hence, closest to the date of invention. Second, this date is robust to applicants' strategies of delaying subsequent applications in other countries since it refers to the earliest date when the patented invention took root in the patent register.

enters a company's patent portfolio is weighted with the number of its forward citations. The resulting citation stock is computed according to:

$$C_t^{stock} = C_t^{flow} + (1-\delta)C_{t-1}^{stock}. \qquad (9)$$

3.3.2.3 Trademark Stocks

Once again, to compute trademark stocks, the declining balance formula is applied (for details, see Hall, 1990). The annual inflows concern only registered CTMs. To collect the trademarks of a specific year, the filing dates of the trademark applications were used. Although the calculation of trademark stocks resembles the computation of knowledge stocks, a major difference remains. Due to technological progress, knowledge assets are prone to erode as time passes. Moreover, patents are granted only for a limited duration. This is addressed through a positive depreciation rate (Hall, 2007). By contrast, trademark rights are not inherently subject to obsolescence. Trademarks, treated as assets, are even likely to become increasingly valuable as time passes. They are, in principle, granted for an infinite period and provide infinite protection if renewal fees are paid regularly. Moreover, by investing in trademarks, companies can cultivate their trademark portfolio and enhance their value as time passes. Therefore, a zero depreciation rate for trademark stocks is assumed resulting in:

$$M_t^{stock} = M_t^{flow} + M_{t-1}^{stock}. \qquad (10)$$

The full history of CTM applications can be observed because the first year of the observation period, 1996, coincides with the commencement of OHIM's operations. Consequently, initial CTM stocks do not have to be approximated. Moreover, a bulk of CTM applications occurred in 1996 since companies sought to gain protection for their already existing trademarks. In fact, the share of applications claiming seniorities was 29.9% in 1996, followed by an immediate decrease in the following years (13.3% in 1997 and 5.5% in 2000). Accordingly, 1996 provides an adequate initial stock for trademarks.

Citation stocks were presented as value-adjusted patent stocks. With trademarks, whose value is also not uniformly distributed (see Barth *et al.*, 1998 concerning brand values), corresponding stocks for their value indicators, W, can be computed by applying Equation 9. The resulting variables are the stocks of Nice classes, seniorities, oppositions brought, and oppositions received.

3.3.2.4 Control Variables

Control variables include year, country, and industry dummies to account for overall valuation effects. Regarding industries, firms have been categorized into 30 different classes using Standard Industrial Classification (SIC) codes. More specifically, firms were initially classified according to their one-digit level using SIC codes. This resulted in ten classes (e.g., 'construction', 'finance, insurance, and real estate', 'manufacturing', 'services', 'transportation, communications, and infrastructure'). The manufacturing class alone held two thirds of all companies and thus was further expanded to the two-digit level, bringing more detail into the categorization (e.g., 'chemicals', 'electronics and components', 'machinery and computer equipment'). Thereafter, 30 industries resulted with each industry sector holding less than approximately 10% of all firms (see Table 11 in Section 3.3.3). This approach was taken to achieve a trade-off between a reasonable number of classes and the breadth of firms arising from the absence of any selection criteria that could have been imposed on industry membership.

3.3.3 Descriptive Statistics

Table 9 sets out descriptive statistics for the 6,757 observations of the final dataset. If only the most recently available observations for each company were used, Table 10 results reporting descriptive statistics for the 1,216 companies in the sample. Major differences between both tables only appear with the stock variables of trademark measures. This is due to the method employed to compute them. For presenting descriptive statistics, I refer to Table 9 as this table is based on the observations later used in the market value regressions.

The dependent variable for the market value equation, Tobin's q, reflects large differences in firm performance. The mean value is 1.43, i.e., the market values of companies exceed the book values. Yet, this is not true for all observations since a substantial share exhibits values below one. The components of Tobin's q, market capitalization, total debt, and total assets show a large variance.[57] Almost half of the observations have a market capitalization of more than 2 billion Euros. Unfortunately, R&D expenditures could not be obtained for all observations. Therefore, a dummy was introduced

[57] The maximum value of assets belongs to *General Electric*.

Table 9: Descriptive Statistics

Variable	Mean	SD	Median	Min.	Max.
Valuation, physical assets, knowledge assets					
Tobin's *q*	1.429	1.172	1.024	0.244	8.435
Market capitalization (million Euros) [1]	9,205.9	25,421.8	2,060.4	0.270	514,443.8
Debt (million Euros) [1]	3,403.1	13,179.0	619.8	0.002	255,373.1
Assets (million Euros) [1]	10,490.9	30,838.6	2,524.8	29.222	542,831.0
No R&D (dummy)	0.409		0.000	0.000	1.000
R&D stock (million Euros) [2]	1,647.4	3960.2	320.4	0.131	40,964.9
R&D stock / assets [2]	0.169	0.141	0.128	0.000	0.677
No patents (dummy)	0.213		0.000	0.000	1.000
Patent stock [2]	149.191	386.907	27.138	0.064	5,431.082
Patent stock / assets [2]	0.025	0.053	0.010	0.000	1.481
Citation stock [2]	134.181	350.074	20.114	0.000	3,500.318
Citation stock / assets [2]	0.019	0.043	0.005	0.000	1.062
CTMs					
CTM stock (= registered applications)	14.751	38.052	5.000	0.000	651.000
CTM stock / assets	0.004	0.007	0.002	0.000	0.048
CTM application stock	17.628	45.521	6.000	0.000	865.000
Share of failed applications	0.096	0.162	0.000	0.000	1.000
Nice classes					
Nice class stock	37.875	118.475	11.000	0.000	3,559.000
Nice class stock / CTM stock	2.331	2.291	2.000	0.000	38.000
Seniorities					
Seniority stock	23.549	111.190	0.000	0.000	2147.000
Seniority stock / CTM stock	1.194	3.043	0.000	0.000	74.000
Oppositions brought					
Opposition brought stock	1.408	12.177	0.000	0.000	485.000
Opposition brought stock / CTM stock	0.039	0.213	0.000	0.000	6.133
Oppositions received					
Opposition received stock	3.961	12.251	1.000	0.000	319.000
Opposition received stock / CTM stock	0.250	0.501	0.091	0.000	10.000
Countries					
US	0.366		0.0	0.0	1.0
Japan	0.226		0.0	0.0	1.0
UK	0.073		0.0	0.0	1.0
Germany	0.052		0.0	0.0	1.0
France	0.046		0.0	0.0	1.0
Italy	0.020		0.0	0.0	1.0
Canada	0.016		0.0	0.0	1.0
Korea	0.013		0.0	0.0	1.0
Switzerland	0.023		0.0	0.0	1.0
Sweden	0.023		0.0	0.0	1.0
Other countries	0.142		0.0	0.0	1.0
Years					
1996	0.126		0.0	0.0	1.0
1997	0.136		0.0	0.0	1.0
1998	0.143		0.0	0.0	1.0
1999	0.150		0.0	0.0	1.0
2000	0.159		0.0	0.0	1.0
2001	0.154		0.0	0.0	1.0
2002	0.133		0.0	0.0	1.0

Notes: N = 6,757 observations. SD = Standard deviation.
[1] Indexed on real 2000 prices using the Ameco database provided by the European Commission.
[2] Companies never performing R&D or possessing patents, respectively, were excluded. R&D is available for 3,991 and patents for 5,318 observations.

Table 10: Descriptive Statistics for Each Company's Last Observation

Variable	Mean	SD	Median	Min.	Max.
Valuation, physical assets, knowledge assets					
Tobin's *q*	1.200	0.967	0.885	0.244	8.377
Market capitalization (million Euros) [1]	7,311.0	19,189.1	1,696.9	6.828	220,134.7
Debt (million Euros) [1]	3,716.8	15,277.2	566.2	0.002	253,359.1
Assets (million Euros) [1]	11,224.2	35,171.5	2,439.7	55.123	521,616.5
No R&D (dummy)	0.395		0.000	0.000	1.000
R&D stock (million Euros) [2]	1,808.3	4,299.8	346.2	0.591	40,677.6
R&D stock / assets [2]	0.194	0.162	0.150	0.001	0.671
No patents (dummy)	0.243		0.000	0.000	1.000
Patent stock [2]	121.893	329.269	21.803	0.064	5058.631
Patent stock / assets [2]	0.019	0.056	0.005	0.000	1.481
Citation stock [2]	106.437	286.860	15.453	0.000	2864.227
Citation stock / assets [2]	0.013	0.041	0.000	0.000	1.062
CTMs					
CTM stock (= registered applications)	22.486	49.946	8.000	0.000	651.000
CTM stock / assets	0.007	0.009	0.003	0.000	0.048
CTM application stock	27.679	61.420	10.000	0.000	865.000
Share of failed applications	0.116	0.151	0.067	0.000	0.875
Nice classes					
Nice class stock	56.036	151.061	20.000	0.000	3559.000
Nice class stock / CTM stock	2.688	1.993	2.250	0.000	29.000
Seniorities					
Seniority stock	23.333	106.510	0.000	0.000	2147.000
Seniority stock / CTM stock	0.797	2.139	0.000	0.000	41.000
Oppositions brought					
Opposition brought stock	2.179	16.781	0.000	0.000	485.000
Opposition brought stock / CTM stock	0.035	0.173	0.000	0.000	5.052
Oppositions received					
Opposition received stock	6.188	16.398	2.000	0.000	319.000
Opposition received stock / CTM stock	0.318	0.576	0.179	0.000	8.000
Countries					
US	0.369		0.0	0.0	1.0
Japan	0.198		0.0	0.0	1.0
UK	0.076		0.0	0.0	1.0
Germany	0.050		0.0	0.0	1.0
France	0.045		0.0	0.0	1.0
Italy	0.023		0.0	0.0	1.0
Canada	0.017		0.0	0.0	1.0
Korea	0.014		0.0	0.0	1.0
Switzerland	0.021		0.0	0.0	1.0
Sweden	0.024		0.0	0.0	1.0
Other countries	0.161		0.0	0.0	1.0

Notes: N = 1,216 companies. For each company, the latest observation has been used in this table (87.6% of these observations regard the years 2001 and 2002). SD = Standard deviation.

[1] Indexed on real 2000 prices using the Ameco database provided by the European Commission.

[2] Companies never performing R&D or possessing patents, respectively, were excluded. R&D is available for 736 companies and patents for 921 companies.

that takes the value one if no R&D data are available. This was the case for 40.9% of all observations.[58] The average ratio of R&D stock to assets is 0.169. The same practice was applied for patents and citations. For less than a quarter of all observations, no European Patents from the PATSTAT database could be assigned. Note that R&D, patent, and citation stocks were computed with the declining balance formula. The maximum patent stock with 5,431 patents, for example, corresponds to 17,000 patents.[59]

Table 9 shows considerable heterogeneity regarding the trademark activities of companies. Both applications and registrations are reported, showing that the average portfolio consists of 14.8 registered CTMs, for which 17.6 CTM applications have been filed. The average share of failed applications is 9.6%. For the description of value indicators, I distinguish between the intensity, W / M, and the stock of each measure, W. Both indicators apply to trademark portfolios at the firm-level, but the former can be interpreted as a relative measure regardless of portfolio size while the latter depicts the accumulated measure in absolute terms. All value indicators show a large variation. The maximum values of these measures indicate that some companies heavily engage in CTM activity. This contrasts with other companies, for which only parsimonious trademark activity was observed. In the average portfolio, each trademark covers 2.3 Nice classes (intensity). Compared to other indicators of trademark value, the breadth is less dispersed. The stock of Nice classes (the accumulated goods and service classes covered by an average portfolio) has a mean of 37.9. Seniorities measure the extent to which a trademark is established at the time of application filing. On average, 23.6 seniorities have been claimed. The seniority intensity occurs at a value of 1.2 seniorities for each trademark in the portfolio indicating that, on average, a CTM claims more than one earlier trademark. The opposition-based metrics show an imbalance between those brought and those received. The reason for this is that lodged oppositions can be observed only when the target company itself owns a CTM. By contrast, oppositions received also include those attacks originating from trademark owners outside the CTM applicant list. On average, 1.4 oppositions are brought, and 4 oppositions are received. Interestingly, the maximum values of these variables show that some companies are engaged in intense battles. Each CTM of the average portfolio brings on average 0.04 oppositions against rivals. The intensity of oppositions

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[58] Descriptive statistics for both R&D stock and R&D stock / assets were computed conditional on R&D availability.

[59] This patent portfolio belongs to *Siemens.*

received, however, reveals that each CTM attracts 0.25 attacks from rivals. A comparison of the intensities of all value indicators points to a large dispersion of seniorities and opposition-based metrics.[60]

Although the companies in the sample were required to be publicly traded, all trademark measures are consistent when compared with the applicants in the full OHIM dataset (see Table 6, described in Chapter 2).[61] Table 9 also reveals that US-based companies account for the largest share of observations, followed by Japan and the UK. This is in line with publications of the OHIM (OHIM, 2004). The ranking of applicants' domiciles is, in principle, consistent with the order shown in the full OHIM dataset. US- and Japan-based corporations, however, are without doubt less prevalent in the OHIM dataset. This divergence may originate from two causes. First, only publicly traded companies were sampled. In Europe, companies are less likely to be listed at stock exchanges (Hall and Oriani, 2006). Second, trademark activities of small and medium-sized enterprises tend to be home-biased. When only larger companies are considered, the share of European firms decreases.

Since no selection criteria regarding industries were imposed, the sample comprises a wide breadth of industries. Table 11 demonstrates the industry differences for selected company and trademark variables. I confined this analysis to 14 industries and subsumed all other industries into one miscellaneous group. Most observations are available for 'chemicals' followed by 'machinery and computer equipment', 'electronics and components', and 'services'. Tobin's q shows strong differences across industries. The highest values occur with 'biotechnology and pharmaceuticals' and 'services'. Industry dummies included in the market value equation account for these differences. The trademark activity across industries also shows large heterogeneity. This may be due to two factors. First, industries producing consumer goods are more engaged in trademark activities compared with producers of intermediate goods. For example,

60 Recall that oppositions are outcomes of current rivalry, in contrast to seniorities, which are outcomes of companies' past trademark activities.

61 For some measures, this is true only for larger applicants as shown in the last two columns of Table 6, which was discussed in Section 2.6.2. Naturally, these larger applicants are the peer group for the publicly listed companies in this study.

Table 11: Industry Characteristics

Industry	Obs.	%	Firms	Ø total assets (million Euros) [1]	Ø Tobin's q	Ø trade-marks	% failed appln. [2]	Per registered CTM [3]			
										Oppositions	
								Nice classes	Senior-ities	Brought	Re-ceived
Chemicals	688	10.2%	109	4,870	1.258	22.3	0.078	1.996	1.577	0.085	0.217
Machinery and computer equipment	659	9.8%	114	5,857	1.283	12.5	0.093	2.456	1.279	0.029	0.195
Electronics and components	659	9.8%	120	7,548	1.665	14.4	0.104	2.011	1.660	0.027	0.195
Services	557	8.2%	121	5,890	2.033	9.6	0.133	2.518	0.714	0.020	0.279
Transportation, communications, and infrastructure	534	7.9%	108	20,973	1.225	12.7	0.117	3.130	0.464	0.030	0.331
Transportation equipment	488	7.2%	79	21,145	0.916	21.5	0.072	2.919	1.106	0.025	0.209
Food and kindred products	393	5.8%	66	6,383	1.513	16.4	0.105	2.051	1.732	0.094	0.305
Instruments for measuring, analyzing, and controlling	345	5.1%	67	5,195	1.663	16.4	0.101	3.201	0.843	0.024	0.223
Retail trade	345	5.1%	59	4,104	1.834	10.4	0.091	1.690	1.075	0.025	0.446
Biotechnology and pharmaceuticals	275	4.1%	47	9,831	3.046	35.6	0.105	1.476	0.941	0.107	0.392
Wholesale trade	215	3.2%	46	7,386	1.003	5.0	0.103	2.785	1.373	0.022	0.262
Primary metal industries	161	2.4%	25	5,330	0.952	9.4	0.080	2.551	1.706	0.008	0.139
Paper and allied products	149	2.2%	24	6,177	1.173	13.0	0.099	1.462	1.110	0.010	0.149
Finance, insurance, and real estate	119	1.8%	27	83,328	0.945	6.0	0.164	1.636	0.330	0.029	0.214
Other industries	1,169	17.3%	204	10,400	1.127	11.2	0.074	2.237	1.274	0.031	0.226
Total	6,757	100%	1,216								
Mean				10,491	1.429	14.8	0.096	2.331	1.194	0.039	0.250

Notes: N = 6,757 observations.

[1] Indexed on real 2000 prices using the Ameco database provided by the European Commission.

[2] To compute these values, the number of CTM applications (i.e., CTM application stock) was, for each industry, divided by the number of CTMs in the portfolio (i.e., CTM stock).

[3] The values in these columns were computed by dividing the stock of Nice classes, the stock of seniorities, the stock of oppositions brought, and the stock of oppositions received by the number of CTMs in the portfolio (i.e., CTM stock).

Table 12: Correlation Matrix

Variables	1.	2.	3.	4.	5.	6.	7.	8.	9.
1. Tobin's *q*									
2. Assets	-0.066***								
3. R&D stock / assets [1]	0.275***	-0.034*							
4. Patent stock / assets [1]	0.021	-0.079***	0.186***						
5. CTM stock	0.106***	0.291***	0.140***	0.029*					
6. CTM stock / assets	0.128***	-0.142***	0.140***	0.123***	0.186***				
7. Nice class stock / CTM stock	-0.046***	0.062***	-0.036*	-0.013	0.040***	0.029*			
8. Seniority stock / CTM stock	0.002	0.014	-0.023	0.025	0.051***	-0.032**	0.002***		
9. Opposition brought stock / CTM stock	0.037**	0.056***	0.038*	0.031*	0.102***	0.055***	0.037**	0.056***	
10. Opposition received stock / CTM stock	0.047***	0.023	0.019	-0.030*	0.014	0.227***	0.047***	0.023	0.019***

Notes: N = 6,757 observations. Pearson correlation coefficients with significance levels: * $0.01 < p \leq 0.05$; ** $0.001 < p \leq 0.01$; *** $p \leq 0.001$.

[1] When computing correlation coefficients based on these variables, companies never performing R&D or possessing patents, respectively, were excluded. R&D is available for 3,991 observations and patents for 5,318 observations.

Table 13: Variance Inflation Factors

Variable	VIF	1 / VIF
CTM stock	1.29	0.77
Assets	1.26	0.79
Opposition received stock / CTM stock	1.14	0.88
CTM stock / assets	1.14	0.88
Nice class stock / CTM stock	1.13	0.89
Share of failed CTM applications	1.08	0.92
R&D stock / assets	1.08	0.92
Seniority stock / CTM stock	1.07	0.93
Patent stock / assets	1.05	0.95
Opposition brought stock / CTM stock	1.03	0.97

Notes: N = 3,696 of 6,757 observations for which all variables, in particular R&D stocks and patent stocks, were available. VIF = variance inflation factors.

trademarks in 'food and kindred products' carry more seniorities than others, and the volumes of oppositions brought and received are above average as well. 'Biotechnology and pharmaceuticals' show a vigorous trademark activity, which has also been noticed by Malmberg (2005). This industry also shows rather high opposition metrics. By contrast, opposition activity is very low for 'primary metal industries'. Second, 'services' or service-related industries tend to have different patterns. 'Transportation, communications, and infrastructure' as well as 'finance, insurance, and real estate' have high application failure rates and few seniorities. This pattern is reversed for 'chemicals'. These phenomena might not be solely due to service-relatedness but they might also be rooted in the maturity of industries and their associated experiences with trademark systems. An investigation of these patterns is an interesting topic for further research.

The correlations (i.e., Pearson correlation coefficients) among the key variables were computed (see Table 12). Correlation coefficients of high magnitude were not observed. To evaluate potential multicollinearity, the variance inflation factors were calculated. Table 13 demonstrates that the maximum variance inflation factor value is 1.29 so that the critical value of ten is not met by far (Kennedy, 1992). Multicollinearity is not an issue for the data presented here.

3.4 Estimation and Discussion of Results

In this section, the market value equation is estimated based on the specifications developed above. Throughout this section, the models rest upon the regression equation

$$\log\frac{V_{it}}{A_{it}} = \log q_{it} + (\sigma - 1)\log A_{it} + \sigma\log\left(1 + \gamma_K\frac{K_{it}}{A_{it}} + \gamma_M\frac{M_{it}}{A_{it}} + \sum_{j=1}^{4}\xi_j\frac{W_{jit}}{M_{it}}\right), \quad (11)$$

with

$$q_{it} = \exp\left(\rho z_{it} + \delta_{1t}d_{1it} + \delta_{2k}d_{2ik} + \delta_{3l}d_{3il} + \delta_0 + \varepsilon_{it}\right). \quad (12)$$

Basically, the model specifications differ in three ways: (i) the operationalization of knowledge assets, K; (ii) the inclusion of trademark stocks, M; and (iii) the inclusion of indicators reflecting trademark value, W / M. This section proceeds in three steps.

Step 1 compares (i) and (ii) and reports 'horse race' regressions[62] to show the explanatory power of knowledge assets and trademarks. To do this, the estimated models include either knowledge assets *or* trademark stocks. The model specifications of step 2 integrate (i) and (ii). Both knowledge assets *and* trademarks are jointly estimated. Additionally, indicators of trademark value (iii) are considered. Step 3 provides comparative statics using the estimation results of step 2. The change in the market value of companies is shown in absolute terms due to shifts in knowledge assets and trademarks.

In all regressions that follow, the dummy variable z addresses those observations where no knowledge assets were observed. When patent data were chosen to operationalize knowledge assets, this coefficient is significantly positive throughout the models while the coefficient for absent or non-reported R&D investments is generally not significant. Both observations are in line with Hall *et al.* (2005). Recall that year, country, and industry dummies are used to control for overall valuation effects (i.e., the regressors d_{1it}, d_{2ik}, and d_{3il}, respectively). Each set of dummy variables is jointly significant throughout all estimations. All models are estimated using NLLS. The elasticities of the key regressors are listed at the bottom of each table.

Step 1 compares the explanatory power of knowledge assets with that of trademarks. These 'horse race' regressions are reported in Table 14. Model M0 (i.e., the baseline model) does not include knowledge assets or trademark stocks. The coefficient of log(assets) indicates diseconomies of scale. Smaller companies (in terms of total assets) are of higher value. In Models M1 through M3, knowledge assets, K, are operationalized by different measures. To permit a comparison of these specifications to those of other studies, no trademark stocks were included. In Model M1, K is captured by R&D stocks, RD^{stock}. Model M2 uses unweighted patent stocks, P^{stock}, while Model M3 uses citation-weighted patent stocks, C^{stock}. Models M1 through M3 show similar results to Hall *et al.* (2005). Regarding Model M1, the coefficient of the R&D intensity (i.e., the ratio of the R&D stock to assets) is highly significant (0.633, $p < 0.001$) and shows that capitalized R&D expenditures are positively related to

62 This term was coined by Hall *et al.* (2005).

Table 14: 'Horse Race' Regressions of Knowledge Assets and Trademark Stocks

Variables (dependent variable: Tobin's q)	Model M0	Model M1	Model M2	Model M3	Model M4
Knowledge assets	-	RD^{stock}	P^{stock}	C^{stock}	-
Trademark stock	-	-	-	-	M^{stock}
log(assets)	-0.0107 *	-0.0155 **	-0.0073	-0.0083	0.0118 *
($\sigma - 1$)	(0.0047)	(0.0047)	(0.0048)	(0.0047)	(0.0051)
R&D stock / assets		0.6334 ***			
λ_K		(0.0900)			
Patent stock / assets			0.4691 **		
λ_K			(0.1815)		
Citation stock / assets				1.9923 ***	
λ_K				(0.2805)	
CTM stock / assets					14.8287 ***
λ_M					(1.5238)
Control variables					
No R&D		-0.0055			
ρ		(0.0192)			
No patents			0.0706 **	0.0791 ***	
ρ			(0.0197)	(0.0196)	
Year dummies	Yes	Yes	Yes	Yes	Yes
Country dummies	Yes	Yes	Yes	Yes	Yes
Industry dummies	Yes	Yes	Yes	Yes	Yes
Constant	0.4304 ***	0.3305 ***	0.3875 ***	0.3702 ***	0.1491 **
δ_0	(0.0483)	(0.0513)	(0.0493)	(0.0488)	(0.0543)
Diagnostics					
R^2	0.291	0.300	0.293	0.298	0.304
Log likelihood	-5,318.78	-5,275.06	-5,309.97	-5,282.70	-5,256.38
2 · Δ(Log likelihood)		87.43 ***	17.62 ***	72.16 ***	124.81 ***
Compared model		M0	M0	M0	M0
Elasticities ∂log(V/A) / ∂log$X$					
R&D stock / assets		0.0594 ***			
λ_K		(0.0080)			
Patent stock / assets			0.0090 **		
λ_K			(0.0034)		
Citation stock / assets				0.0291 ***	
λ_K				(0.0040)	
CTM stock / assets					0.0586 ***
λ_M					(0.0057)

Notes: N = 6,757 observations. Estimation method: NLLS. Robust standard errors in parentheses. Significance levels: * $0.01 < p \leq 0.05$; ** $0.001 < p \leq 0.01$; *** $p \leq 0.001$. Reference group for industry: 'electronics and components'. Reference country: US. Reference year: 2002.

firms' market value. This finding confirms those of other studies that found similar values (Hall, 1993a, 1993b; Hall *et al.*, 2007; Megna and Klock, 1993). Model M2 uses patent stocks to operationalize knowledge assets. The coefficient of the patent intensity (i.e., the ratio of the patent stock to assets) is positive and significant (0.469, $p < 0.01$). It will turn out in step 2 that this coefficient becomes insignificant when trademark stocks are additionally included. In Model M3, which uses citation-weighted patent stocks, the coefficient is significantly positive (1.992, $p < 0.001$). In Model M4, which includes trademark stocks but not knowledge assets, the coefficient of the trademark intensity (i.e., the ratio of the trademark stock to assets) is positive and highly significant (14.829, $p < 0.001$). The elasticity of this variable is higher than the elasticities of both weighted and unweighted patent stocks, but of similar size to that of R&D stocks. To analyze the explanatory power of knowledge assets and trademark stocks, the R^2 measures and the likelihood-ratio tests are considered. Compared to the baseline specification M0, this measure increases significantly from 0.291 to 0.300 when R&D stocks are included (Model M1). Unweighted patent stocks do not add much explanatory power since R^2 yields only 0.293. According to the evidence presented by Hall *et al.* (2005), citation-weighted patent stocks add more value than unweighted patent stocks. The R^2 of Model M3 is 0.298. When trademark stocks are included (Model M4), the R^2 is 0.304, the highest R^2 value reported so far.

In step 2, the estimated specifications are based on Models M1 through M3 of step 1, but, in addition to knowledge assets, they also include trademark measures. Table 15 reports these estimations. For each measure of knowledge assets, two models are provided: one including trademark stocks, and the other including both trademark stocks and their value indicators. Two main findings can be drawn from the estimations reported in Table 15. First, trademarks are economically valued, a finding robust to different measures of knowledge assets. Similar to knowledge assets, trademark measures add further value when explaining Tobin's *q*. Second, seniorities and oppositions brought reflect the dispersed value of trademarks.

Throughout all specifications of Table 15, the coefficients for trademark stocks are strongly significant and positive (13.878, $p < 0.001$ in Model M1a). This supports the evidence provided by Greenhalgh and Rogers (2006a), who also find that, controlling for firm size, larger trademark portfolios are associated with higher firm values. Interpreting the coefficient as the relative shadow value of trademarks to physical assets indicates that one CTM is equivalent to 13.9 million Euros in assets. Despite varying measures of knowledge assets, the great robustness of this coefficient is notable. A comparison of the joint inclusion of knowledge assets and trademark stocks in this step with the 'horse race' regressions of the previous step shows that the coefficients for knowledge assets decrease in size when trademark stocks are introduced. Trademark stocks thus carry information that is partly embodied in knowledge assets. This can be explained by companies' efforts in new product development, which span the processes of research, development, and market introduction. Knowledge assets enable the creation of new products, and trademarks support their sale.

Table 15: Market Value as a Function of Knowledge Assets and Trademark Stocks

Variables (dependent variable: Tobin's q)	Model M1a	Model M1b	Model M2a	Model M2b	Model M3a	Model M3b
Knowledge assets	RD^{stock}	RD^{stock}	P^{stock}	P^{stock}	C^{stock}	C^{stock}
Trademark stock	M^{stock}	M^{stock}	M^{stock}	M^{stock}	M^{stock}	M^{stock}
log(assets)	0.0053	0.0026	0.0146 **	0.0122 *	0.0125 *	0.0103
$(\sigma - 1)$	(0.0051)	(0.0053)	(0.0051)	(0.0053)	(0.0051)	(0.0053)
R&D stock / assets	0.5337 ***	0.5409 ***				
λ_K	(0.0906)	(0.0910)				
Patent stock / assets			0.2479	0.2303		
λ_K			(0.1770)	(0.1748)		
Citation stock / assets					1.6514 ***	1.5960 ***
λ_K					(0.2811)	(0.2798)
CTM stock / assets	13.8781 ***	13.2483 ***	14.7066 ***	14.1260 ***	13.7485 ***	13.2393 ***
λ_M	(1.5505)	(1.5432)	(1.5306)	(1.5197)	(1.5263)	(1.5174)
Nice class stock / CTM stock		-0.0059		-0.0066 *		-0.0063 *
ξ_1		(0.0032)		(0.0031)		(0.0031)
Seniority stock / CTM stock		0.0083 **		0.0077 **		0.0078 **
ξ_2		(0.0028)		(0.0026)		(0.0027)
Opposition brought stock / CTM stock		0.1218 *		0.1219 **		0.1123 *
ξ_3		(0.0484)		(0.0465)		(0.0473)
Opposition received stock / CTM stock		0.0204		0.0175		0.0186
ξ_4		(0.0151)		(0.0146)		(0.0147)
Control variables						
No R&D	-0.0175	-0.0149				
ρ	(0.0189)	(0.0189)				
No patents			0.0680 **	0.0697 **	0.0759 ***	0.0773 ***
ρ			(0.0195)	(0.0196)	(0.0195)	(0.0195)
Year dummies	Yes	Yes	Yes	Yes	Yes	Yes
Country dummies	Yes	Yes	Yes	Yes	Yes	Yes
Industry dummies	Yes	Yes	Yes	Yes	Yes	Yes
Constant	0.0979	0.1178 *	0.1179 *	0.1396 *	0.1175 *	0.1368 *
δ_0	(0.0563)	(0.0566)	(0.0549)	(0.0552)	(0.0547)	(0.0550)
Diagnostics						
R^2	0.310	0.313	0.305	0.307	0.309	0.311
Log likelihood	-5,224.13	-5,213.40	-5,249.78	-5,238.78	-5,230.64	-5,220.69
$2 \cdot \Delta$(Log likelihood)	101.87 ***	123.33 ***	120.38 ***	142.37 ***	104.12 ***	124.03 ***
Compared model	M1	M1	M2	M2	M3	M3
Elasticities $\partial \log(V/A)/\partial \log X$						
R&D stock / assets	0.0479 ***	0.0483 ***				
λ_K	(0.0078)	(0.0077)				
Patent stock / assets			0.0045	0.0041		
λ_K			(0.0032)	(0.0032)		
Citation stock / assets					0.0230 ***	0.0222 ***
λ_K					(0.0038)	(0.0038)
CTM stock / assets	0.0524 ***	0.0498 ***	0.0579 ***	0.0556 ***	0.0533 ***	0.0513 ***
λ_M	(0.0056)	(0.0056)	(0.0057)	(0.0057)	(0.0056)	(0.0056)
Nice class stock / CTM stock		-0.0124		-0.0145 *		-0.0136 *
ξ_1		(0.0068)		(0.0068)		(0.0067)
Seniority stock / CTM stock		0.0089 **		0.0087 **		0.0086 **
ξ_2		(0.0029)		(0.0030)		(0.0030)
Opposition brought stock / CTM stock		0.0043 *		0.0045 **		0.0041 *
ξ_3		(0.0017)		(0.0017)		(0.0017)
Opposition received stock / CTM stock		0.0046		0.0041		0.0043
ξ_4		(0.0034)		(0.0034)		(0.0034)

Notes: N = 6,757 observations. Estimation method: NLLS. Robust standard errors in parentheses. Significance levels: * $0.01 < p \leq 0.05$; ** $0.001 < p \leq 0.01$; *** $p \leq 0.001$. Reference group for industry: 'electronics and components'. Reference country: US. Reference year: 2002.

Interestingly, unweighted patent stocks lose their significance if trademark stocks are added. To elaborate on this finding, the different measures of knowledge assets are compared. Model M1a includes both R&D and trademark stocks. The coefficient of the former is positive and highly significant (0.534, $p < 0.001$ in Model M1a), as is that of the latter. Here, one Euro spent on R&D is equivalent to 0.53 Euros in physical assets. In Model M2a, knowledge assets are represented by patent stocks. The coefficient for trademark stocks remains significantly positive but the unweighted patent stocks are insignificant. This is interesting because the patent stock was significantly positive in Model M2, in which trademark stocks were omitted. When citation stocks are used to operationalize knowledge stocks (Model M3a), however, this patent measure, now adjusted for patents' value, is again positive and highly significant (1.651, $p < 0.001$ in Model M3a). One patent citation is equivalent to 1.65 million Euros in physical assets. The quality of patents carries new information that is not captured by trademarks. This finding is explained by the idea that trademark and unweighted patent stocks have common information. Patents need to be adjusted for their value to be informative. The loss of significance regarding unweighted patent stocks may be interpreted as follows. Investors can more easily draw expectations about future cash flows from trademarks than from the more uncertain future cash flows arising from patents. This is explained by the great information asymmetries generated by R&D investments (Aboody and Lev, 2000; Hall, 2000). Companies register trademarks only if they have products and services ready to be sold. Whether patents, interpreted by their mere number, result in cash flows is uncertain. Pure patent counts seem to reflect meaningless IP activity and do not add value from an investor's perspective. The quality of patents, however, is informative for the financial market. This finding adds to the conclusions of Hall *et al.* (2005), who found citation-weighted patents to be more informative than patent counts. The elasticities show how a 1% change in the regressor of interest relates to a percentage change in Tobin's q. A 10% increase in the CTM stock is associated with a 0.52% higher market value (Model M1a). A 10% higher R&D stock is linked with a 0.48% higher market value (Model M2a), but a 10% increase in citation stocks relates to an increase in market value of only 0.23% (Model M3a).

The four value indicators of trademarks are included in Models M1b, M2b, and M3b as intensities that characterize trademark portfolios, W / M. The regressors contained in Models M1a, M2a, and M3a, which excluded value indicators, remain relatively unchanged. The value indicators provide new information and are rather robust throughout the models, but not all of them behave as expected. First, the breadth of trademarks is captured by the ratio of the Nice class stock to trademark stock. Unexpectedly, this regressor shows no significance in Model M1b and even appears to be significantly negative in Models M2b and M3b (-0.0063, $p < 0.05$ in Model M3b). Broader trademarks do not have a higher economic value. The negative coefficients, however, may be interpreted in another manner. Assuming that the breadth of trademarks reflects firms' diversification, a negative coefficient may indicate that widely diversified companies experience a discount at stock markets (e.g., Montgomery and Wernerfelt, 1988). Second, the coefficient for the ratio of the seniorities to trademarks, as predicted, is highly significant (0.0078, $p < 0.01$ in Model M3b). This coefficient shows that those trademarks that are rooted in earlier trademark rights of other jurisdictions are of higher value. A company receives a higher valuation in the stock market if it holds established trademarks. This is because those trademarks reflect a higher degree of familiarity or awareness. A causal relationship can be assumed because seniorities clearly point to past trademark activities. Third, the number of oppositions brought by a firm against rivals is, as expected, significantly positive (0.112, $p < 0.05$ in Model M3b). The financial market values companies that lodge oppositions against rivals. This can primarily be explained by firms' efforts to actively protect their acquired brand assets and their trademark base by filing oppositions against rivals. If a company owns valuable trademarks, it will defend them more vigorously. Furthermore, it is also possible that the financial market values aggressive strategies against rivals.[63] Fourth, the coefficient regarding oppositions received by a firm is insignificant. Accordingly, attacks by rivals should not be interpreted as an acknowledgement of the potential value of a trademark. This is different from patents where oppositions received are informative about their value (Harhoff *et al.*, 2003a).

The coefficient of log(assets) provides evidence about the homogeneity of the value function. It also allows one to investigate how physical assets, knowledge assets and trademarks are related to each other. In Model M0, this coefficient is negatively significant, indicating diseconomies of scale. Smaller companies, as measured by total assets, have a higher Tobin's *q*. When R&D stocks are added (Model M1), this coefficient still points to diseconomies of scale. Adding trademark stocks (Model M1a) makes the coefficient insignificant, pointing to constant returns to scale. Again, compared with Model M0, adding citation-weighted patent stocks (Model M3) makes the

[63] Although a causal relationship cannot be taken for granted, companies' engagement in such activities is likely to help protect their assets against impairment. This, in turn, influences investors' assessment of companies' future performance.

coefficient insignificant. Adding trademark stocks (Model M3a) even renders the coefficient significantly positive, indicating economies of scale. Accordingly, the value function is not homogeneous of degree one and, thus, it can be said that the sum is more than its parts. The behavior of this coefficient provides some evidence for the conjecture that trademarks are complementary to patents and physical assets.

Step 3 provides comparative statics and describes how changes in knowledge assets and trademark stocks are reflected in the market value of firms in absolute terms. Due to the skewness of firm size, as measured by total assets, median values of the variables are used. The coefficients of Models M1a and M3a were applied to establish estimations of the value function based on Equation 3. Then, Equations 13 and 14 result:

$$V(RD^{stock}, M^{stock}) = 1.1731\left(619.764 + 0.5337 \cdot RD^{stock} + 13.8781 \cdot M^{stock}\right), \quad (13)$$

and

$$V(C^{stock}, M^{stock}) = 1.1329\left(619.764 + 1.6514 \cdot C^{stock} + 13.7485 \cdot M^{stock}\right)^{1.0125}. \quad (14)$$

In Equation 13, the estimated value of q_{it} is 1.1731. To obtain this value, note that Equation 2 can also be written as $\mathrm{E}[q_{it}] = \mathrm{E}[\exp(y_t + c_k + m_l + u_{it})]$ and $\mathrm{E}[q_{it}] = \mathrm{E}[\exp(y_t + c_k + m_l)]\ \mathrm{E}[\exp(u_{it})]$. According to Wooldridge (2003, p. 208), the expectation of $\exp(u)$, $\mathrm{E}[\exp(u)]$, is $\exp(\sigma^2/2)$. σ^2 is the variance of u. If $\hat{\sigma}^2$ is an unbiased estimator of σ^2 and $Q = V/A$, $\exp(\hat{\sigma}^2/2)$ can be obtained from predicting Q with $\hat{Q} = \exp(\hat{\sigma}^2/2)\exp(\widehat{\log} Q)$. Here, $\widehat{\log} Q$ is the prediction of $\log Q$, obtained by the 'delta' method and using the estimated coefficients of Model M1a, taking the non-linearity of this model into account. The 'delta' method is also used to compute the median of the predictions of $\exp(y_t + c_k + m_l)$. Applying the regression results of Model M1a yields $q_{it} = 0.9810 \cdot 1.1958 = 1.1731$. The same procedure was employed to predict $q_{it} = 0.9479 \cdot 1.1952 = 1.1329$ for Equation 14. Both equations can now be used to assess the fraction of company values attributable to knowledge assets or trademark portfolios.

As Table 16 reports, insertion of median values of R&D stock, RD^{stock}, and trademark stock, M^{stock}, results in a firm value of 1,009.1 million Euros (Equation 13). If R&D stocks are exchanged with citation stocks (Equation 14), the resulting firm value is 887.7 million Euros. Both equations can be used to assess how the market value of companies is associated with changing knowledge assets and trademark portfolios (see Table 16). Note that these values are sensitive to the depreciation rates used to compute the stock variables. Accordingly, these calculations should be interpreted cautiously.

Table 16: Market Value of Knowledge Assets and Trademark Portfolios

		Independent variables			Dependent variable		
Equation	**Computation**	RD^{stock}	C^{stock}	M^{stock}	V	ΔV	%
(13)	1. Median values	320.4		5.0	1,009.1		
	2. Median values, RD^{stock} doubled	640.8		5.0	1,209.7	200.6	19.9%
	3. Median values, M^{stock} doubled	320.4		10.0	1,090.5	81.4	8.1%
(14)	4. Median values		20.1	5.0	887.7		
	5. Median values, C^{stock} doubled		40.2	5.0	929.1	41.4	4.7%
	6. Median values, M^{stock} doubled		20.1	10.0	973.4	85.7	9.6%

Using R&D stocks as knowledge assets, a doubling of the trademark stock is associated with an increased market value of 81.4 million Euros.[64] Conversely, if the R&D stock is doubled, the market value increases by 200.6 million Euros. For Equation 14, where value-adjusted patent stocks proxy knowledge assets, the same increase of the trademark stock translates to a market value increase of 85.7 million Euros. In contrast, a doubled citation stock yields a market value increase of 41.4 million Euros. Finally, the contribution of total knowledge assets can be shown if their total value is related to the company's market value. On average, the share of knowledge assets in terms of R&D stocks equals 19.9% of a company's market value. Citation stocks represent 4.7% on average. Similarly, trademark portfolios make up an average of 8.1% of the market value in the R&D specification and 9.6% in the citation specification. In comparison, Brand Finance (2007), a major brand valuation statistic, presents shares of brand values in relation to enterprise values. For these brands, the median share equals 14%, but this median share is likely to be upward biased because only the worlds' 250 most valuable brands were assessed. In sum, both trademarks and knowledge assets are valued and a substantial share of companies' market values can be attributed to them. The next section presents conclusions of these results.

[64] Similarly, a zero trademark stock, *ceteris paribus*, corresponds to a market value decrease of the same magnitude.

3.5 Conclusions

Trademark rights are an essential instrument for companies to protect their acquired assets against impairment. As Phillips (2003, p. 641) states, “the trademark is the legal anchor which protects the brand from drifting away from its owner’s control.” Correspondingly, rights conferred by trademarks are a vehicle used by companies to control a brand’s development and to exploit the exclusivity gained through potentially large investments. However, trademark rights have rarely been examined in economics compared to the extensive body of literature on patents (Mendonça *et al.*, 2004). Only few studies have analyzed these intangibles jointly (Bosworth and Rogers, 2001; Greenhalgh and Rogers, 2006a, 2006b). This chapter did so and addressed the economic value of both trademarks and knowledge assets. More specifically, it investigated whether the market value of publicly traded companies is associated with their trademark portfolios. Furthermore, the market valuation of R&D and patents as knowledge assets was examined. Patents are mainly held by manufacturing companies, but, in the case of trademarks, no industry restrictions need to be imposed. Accordingly, a broader range of companies could be analyzed in this study, including retail and service companies. To assess the economic value of trademarks in more detail, indicators reflecting their value were obtained from trademark registration files. Except for von Graevenitz (2007), these indicators have not yet been used in research. The present study is the first to analyze their contribution to companies’ market values and to scrutinize their capability to reflect trademark value. This study adds to the understanding of how the financial market values trademarks and knowledge assets. Since market-based intangibles are also regarded, it adds to and complements the stream of literature focusing on knowledge assets (e.g., Blundell *et al.*, 1999; Cockburn and Griliches, 1988; Griliches, 1981; Hall *et al.*, 2005).

The results obtained in this study may provide valuable insights for both researchers and managers. It was shown that financial investors value companies’ investments in both knowledge assets and trademarks since both are positively associated with firm value in the financial market. These results generally hold for two measures of knowledge assets: capitalized R&D expenditures and patents. Considering capitalized R&D expenditures and trademarks jointly, R&D investments capture on average 19.9% and trademark portfolios 8.1% of companies’ market value. One trademark has been estimated to be equivalent to 13.9 million Euros of physical assets and one Euro invested in R&D is equivalent to 0.53 Euros in assets. Considering patents and trademarks jointly, patents provide new information only if their value is considered by employing citation-weighted patent stocks. Then, patent portfolios represent 4.7% of the firm value and one patent citation corresponds to 1.65 million Euros of physical assets. Hall *et al.* (2005) found that both unweighted and weighted patent stocks were significant but they did not consider trademarks. Their results were replicated in this study when trademarks were excluded. In line with their results, value-adjusted patent stocks were more informative than pure patent counts, yet the significance of unweighted patent stocks disappeared when trademarks were included. This relationship suggests that trademark stocks carry information that is also embodied in unweighted patent stocks. It may be due to companies' activities in new product development, which involve both patents and trademarks. Financial investors do not consider the mere number of patent documents, but instead, they assess patents' inherent value and implicitly place an economic value on those patents being of higher value.

The indicators used in this study to account for the greatly dispersed value of trademarks have considerable explanatory power. First, the breadth of trademarks, as indicated by the number of product and service classes for which a trademark is registered, measures the diversification of companies. The results showed that the financial market places a discount on widely diversified companies. Second, seniorities were found to be informative about trademark value. They reflect the diffusion of trademarks and consumers' potential awareness of them. Third, more valuable trademarks are more vigorously protected by their owners through lodging oppositions against rivals. Consequently, oppositions as legal instruments to maintain a trademark's exclusivity or to weaken competitors' branding aspirations are of economic relevance. Fourth, oppositions received from rivals are not informative about trademark value. Thus, this measure should not be interpreted as reflecting third party endorsements of the value of a company's trademarks.

Although this study provides novel results, the following limitations are noted. Two issues arise from the fact that only CTMs were considered. First, trademark portfolios may also contain a substantial share of national trademark rights. Consequently, a potential bias cannot be excluded. Due to the size of the sampled companies, this bias is probably small because large companies are likely to mainly hold CTMs. Second, the observation period used here began in 1996 when CTMs were introduced. It may have been interesting to include previously registered trademark rights. Both issues could be addressed if international trademark data or the data of national jurisdictions were available, which unfortunately was not the case. The empirical analysis reported herein rests upon a dataset drawn from several sources. The assignment of trademarks and patents to companies is critical to build coherent IP portfolios at the firm-level. Though a high degree of reliability could be achieved by the manual creation of company name patterns to match trademarks and patents, the possibility that some patents or trademarks were not assigned to the correct company or not assigned at all cannot be ruled out. Although I accounted for potential misspellings and notable ownership changes, this procedure could be improved to account for the full variety of misspellings, full ownership changes, and multi-level corporate structures. Obviously, much work has to be done to optimize those algorithms.

Avenues for further research concern the relationship among technologies, products, and services, for example, the correspondence of new trademark applications with new products (Malmberg, 2005). In contrast to patents, trademarks do not require restrictions regarding companies' industry membership since they are registrable for the whole range of products and services. A decomposition of the trademark portfolio according to the various product and service classes could reveal interesting results regarding the way companies endow their products with trademark rights. Accordingly, the economic return to product-accompanying services and service-accompanying products could be assessed. Industry-specific investigations of the economic value of trademarks could also reveal interesting differences. Another fruitful area of future research involves companies' efforts to protect their assets through different kinds of IP rights. The relationship between patent rights and trademark rights clearly requires further examination. Companies' strategies of holding rights of several IP domains have rarely been studied and demand attention. Anecdotal evidence (Rujas, 1999) has indicated that trademarks are complementary to patents. In all, our understanding of the economic role of trademarks and the way companies employ them is still in its roots. This is contrasted by companies, who have used trademarks since many decades.

4 Trademark Filing Strategies and Their Valuation: Creating, Hedging, Modernizing, and Extending Brands

4.1 Introduction

Financial markets value companies based on the future cash flows that are generated by their assets. These assets include not only tangibles but also intangibles such as knowledge assets or brands. Both of these types of assets play an important role in the valuation of a company but intangibles are generally difficult to price. Understanding the contribution of knowledge assets to the market value of companies has a long history, and researchers have often used R&D expenditures and patent data when estimating the value of these assets (e.g., Connolly and Hirschey, 1988; Griliches, 1981; Hall, 2000; Hall *et al.*, 2007). Contrary to that, the contribution of brands to companies' market values has been less rigorously researched. There are some notable exceptions, in which researchers empirically investigated the relation between brands and company values in financial markets (e.g., Barth *et al.*, 1998; Kallapur and Kwan, 2004; Simon and Sullivan, 1993). Researchers in this area have employed different measures at the brand-level to analyze the determinants of brand value and to estimate the share of brand assets in total company value.

Brands and their underlying trademarks are important assets to companies as they have the potential to influence consumers' product choices (Agarwal and Rao, 1996). From the perspective of consumers, brands facilitate consumer choice by providing information, and they are generally taken to transmit quality signals and thus to serve as a vehicle for reducing perceived risk (Economides, 1988; Montgomery and Wernerfelt, 1992; Wernerfelt, 1988).

Despite the importance of brands to companies, proving its relevance to company performance is not an easy endeavor leading Aaker to write (1991, p. 15): "The value of brand-building activities on future performance is not easy to demonstrate. The challenge is to understand better the links between brand assets and future performance, so that brand-building activities can be justified." Brand values are affected by corporate brand management, which involves decisions such as the creation of new brands or the use of existing ones when new products are introduced (Farquhar *et al.*, 1992). Understanding the link between brand management and the valuation of brand assets allows researchers and managers to assess how decisions in corporate brand management contribute to company value and, in turn, how financial markets value the brands that a company owns.

Insofar as brand management involves issues such as brand creation and development, it organizes the allocation of brands to products. A firm can decide, for example, to create narrow brands that are applied to only one or very few products, or it can create umbrella brands that span broad product categories or even a company's entire product portfolio. Since new trademarks need to be filed to protect these brands (i.e., to exclude others from unauthorized use, European Council, 1993, Art. 9), activities in brand management will be, to a large extent, mirrored in trademark registers.

Brands are constructs that are perceived by consumers as possessing both visible and invisible aspects. The latter aspects include the brand image or brand reputation. Visible factors mainly concern the trademarks that underlie a brand but a brand does not necessarily need to be associated with a single trademark. Instead, a plurality of trademarks can be associated with a brand in order to take on different appearances or to include different components (Mendonça *et al.*, 2004). This is well illustrated, for example, by the brand *Coca-Cola* which represents a bundle of trademarks, including several protected word marks and several protected graphical signs. Since brand management is reflected in trademark data, it is surprising that researchers have never widened the scope of brand management to include trademarks as the legal basis of brands.

Related research characterizes brands as having the potential to differentiate a product from those of competitors. The differentiation potential of a brand is of great importance because brands affect consumers' product choices or command price premia (Agarwal and Rao, 1996; Ailawadi *et al.*, 2003; Swaminathan *et al.*, 2001). The reason *why* consumers are in the position to perceive brands as being distinctive is rooted in the trademark rights that protect those brands. A trademark allows its owner to prevent third parties from using it (European Council, 1993, Art. 9). Trademarks are hence the legal anchors of brands (Phillips, 2003). The link between the differentiation potential of a brand and the associated trademarks is explained as follows. Trademark law requires a brand to be inherently distinctive, meaning that it needs to be "capable of distinguishing the goods or services" (European Council, 1993, Art. 4) of one company from those of competitors. Trademark applications that do not comply with this requirement are not granted. If a competitor files a trademark application that is identical or confusingly similar to an already registered trademark, the proprietor of the existing trademark can stop the competitor's application from being granted (European Council, 1993, Art. 8). Correspondingly, competitors cannot get protection for an identical or similar trademark. Moreover, trademarks ensure that their owners can control their use since a company can take legal actions if a competitor counterfeits products or otherwise seeks to unfairly appropriate a trademark's value. It is this requirement of distinctiveness enshrined in trademark law, and the legal protection that it affords, that preserves a brand's communicative power to current and potential consumers and allows it to proceed free from interference. The trademarks that underlie a brand endow their proprietors with the legal instruments to effectively maintain a brand's differentiation potential. All advertising activities, product promotions, etc. need to comply with the legal grounds set up by trademarks. Trademarks are hence the building blocks of brands in that they ensure the value of a brand and protect this value against impairment. As trademarks are the fundamental constituents of brands, their characteristics and the ways in which they support and form brands should be analyzed.

The objective of this chapter is to investigate how brand management is associated with trademark filing strategies and how the benefits of these strategies are valued in financial markets. This unveils the importance of different kinds of trademarks and how they are affiliated with brands. Moreover, assessing the valuation of trademark portfolios based on companies' valuations in stock markets provides insights into what investors expect to be profitable strategies. This study seeks to address the following questions: First, which trademark filing strategies can be identified, and do they reflect corporate brand management? Second, how can companies' trademark portfolios be examined to reveal the inherent structure of these portfolios? Third, is the valuation of companies in financial markets related to the trademark filing strategies they employ? To address these questions, corporate brand management needs to be reconciled with the complex structure of trademark portfolios. Based on the trademark filing strategies companies employed when building their portfolios, I derive portfolio characteristics which I then link to companies' valuations in financial markets. Companies' market values in stock markets are forward-looking performance measures that reflect future expectations about company success. Investors examine companies' assets (including brands) in order to estimate how these assets might generate future cash flows. The expectations investors form ultimately materialize in stock prices. Adopting a Tobin's *q* format derived from the market value approach then allows one to examine market-related intangible assets. To my knowledge, this is the first study linking trademarks and their filing strategies to financial markets by considering the inherent structure of trademark portfolios. This also allows scrutinizing the relationship between trademarks and brands. A dataset is compiled that includes accounting, financial, and trademark data for the world's largest publicly listed corporations. The dataset contains 1,735 observations from the year 2004 and is cross-sectional in nature. Based on this dataset, NLLS regression techniques are used to estimate the market value equation. To build corporate trademark portfolios and to subsequently reveal their structures, I use applications for CTMs. CTMs, which are pan-EU trademark rights, are filed by companies that seek protection in the entire territory of the EU. The CTM register used here was provided by the OHIM and included all CTM applications filed until the end of 2004.

This study makes several contributions to the existing literature. Four different trademark filing strategies were identified and, for the purpose of this study, named as follows: (i) creating, (ii) hedging, (iii) modernizing, and (iv) extending brands. With the first filing strategy, *creating brands*, companies file a trademark to protect brands that are newly created, for example, if a new product is to be introduced. The other three strategies concern the development of already existing brands. *Hedging brands* refers to those cases where a company simultaneously files highly interrelated trademarks to support a brand. Companies adopt such a strategy to separately protect multiple facets of the same sign or brand name. *Modernizing brands* refers to those cases where a company files trademarks to update or maintain the appearance of a brand. This is necessary to prevent the symbols that represent a brand from becoming obsolete and to protect established brands against erosion and impairment.[65] *Extending brands* refers to those cases where established brands are applied to new products in both familiar and new markets. When launching a new product in a familiar market (line extensions) or in an unknown market (brand extensions), a link to established brands allows consumers to infer the quality of these new products by drawing on their past experiences with the brand. Interestingly, although each trademark filing strategy may have its justification from the company's perspective, only modernizing and extending brands were found to be valued in financial markets when estimating the market value equation. This finding is explained by the potential impact of these two

[65] Examples where such strategies were applied include brands like *Lufthansa* and *Shell*, whose appearances (i.e., their trademarks) changed several times over the last decades.

strategies on future cash flows, on which investors in financial markets base their appraisals of companies. Modernizing strategies strengthen existing brands and, thus, support revenue streams from existing products. Moreover, new consumers may be attracted by a brand that is not subject to obsolescence because the company commits to asserting and enhancing its assets. Extending strategies may induce future cash flows as the use of established brands for new products both increases the probability of product success and disseminates existing price premia. Furthermore, as brands become broadened through extending strategies, advertising efficiencies can be gained.

Another important contribution of this work is the presentation of a technique that dissolves companies' trademark portfolios and maps trademark applications to different roles and filing strategies. This technique unveils groups of interrelated trademarks within trademark portfolios, which I call trademark families. While trademark families themselves reflect brands, their sizes indicate both the degree of each brand's legal protection and their portfolio relevance. This technique is appealing for at least three reasons: First, the combination of this technique with the market value approach depends only on objective data. This concerns Tobin's q as the dependent variable to measure company performance and the various regressors. The need for studies that employ 'hard' data has been noted as the marketing and business research often evaluates brand decisions in hypothetical laboratory settings (Reddy *et al.*, 1994). Only few studies have used 'hard' data to investigate the relation between brands and company values (e.g., Kallapur and Kwan, 2004; Lane and Jacobson, 1995; Rao *et al.*, 2004). Second, it has been suggested that studies involving brand management decisions should be extended to other and broader product categories, instead of focusing on single products or narrow categories (e.g., Sullivan, 1992). As trademarks can be registered for the whole range of products and services, the technique of uncovering the structure of trademark portfolios is not restricted to specific industries. Thus, when compiling the dataset for this study, no restriction regarding industry membership was imposed. Third, researchers have noted a lack of systematic empirical work in this field. It has been stated that instead of focusing on single brands, researchers should consider entire portfolios containing multiple brands since measurement errors occur when combining brand-level with firm-level data (Aaker and Jacobson, 1994; Simon and Sullivan, 1993).[66] As a consequence of such objections, researchers have called for research on more complex branding strategies that might include, for example, the histories of brand extensions instead of focusing on single decisions (Aaker and Keller, 1990; Reddy *et al.*, 1994). The technique proposed in this study complies with these research needs because trademark portfolios reflect multiple brands and also reveal the ways in which companies have developed them.

This chapter is organized as follows. Section 4.2 explains how brand management decisions may affect companies' valuation in financial markets. The decisions involved in brand management are characterized and then linked to the filing of trademark applications. The idea is to use brand management as a 'connector' between trademark filing strategies and brand assets. Section 4.3 presents the technique of revealing the structure of trademark portfolios to uncover both the brands protected therein and the underlying trademark filing strategies that produced these portfolios. For several companies, the trademark portfolios are presented in detail. Section 4.4 describes the market value approach and presents how trademark portfolio characteristics are accommodated in the market value equation. Section 4.5 presents how the data have been compiled and unveils descriptive statistics of the dataset. In Section 4.6, I estimate the market value equation and present the results along with a discussion of them. Section 4.7 summarizes the main results, addresses limitations of this work, and identifies fruitful avenues for further research.

4.2 The Connection Between Market Value, Brand Management, and Trademarks

This section explains brands as an asset class (Section 4.2.1). It then describes how brand assets are linked to brand management (Section 4.2.2) and that decisions to create new brands or to develop existing ones (e.g., by means of line extension or brand extension) are among the main issues of brand management (Section 4.2.3). The development of brands would not be possible without transferable reputation and informational leverage (Section 4.2.4). Finally, it is discussed how brand management is reflected in trademark filing strategies (Section 4.2.5).

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66 Imagine a company like *Procter & Gamble* holding a large portfolio of brands (e.g., *Duracell*, *Gillette*, *Lenor*, *Pampers*). Problems may arise when data on single brands (e.g., price premia) are combined with firm-level data (e.g., company values).

4.2.1 Brand Assets

Brands belong to the class of intangible assets (Kapferer, 2004; Lev, 2001). The main function of a brand is differentiation. From the company's perspective, brands enable consumers to identify their products and services as well as to differentiate them from the products and services of competing businesses. Brands also induce perceptions by consumers. Bennett (1995) and Dibb *et al.* (1997) state that a brand is a name, term, design, symbol, or any other feature that identifies a company's product or service as distinct from those of other companies. Brands differ from trademarks in two main ways: First, a brand can comprise not only a single name, term, design, or symbol, which regularly are the trademarks, but any combination thereof. Hence, although not explicitly stated in the aforementioned definition, a brand can represent a bundle of trademarks. Second, consumers' perceptions of a brand are formed not only by signs that can be graphically represented like trademarks (European Council, 1993, Art. 4) but also by intangibles such as reputation and image (Ailawadi *et al.*, 2003). Companies rely on trademarks to codify and communicate brands because trademark rights are the fundament of differentiation. That is because they, as legal instruments, assure that signs or symbols cannot be copied or imitated by competitors. For consumers, however, the definition of a brand focuses on the perceived added valued delivered by the brand not on the graphical trademark itself (Farquhar, 1989). A brand can be viewed as a feature of the product both inducing consumer perceptions and affecting consumer choice (Agarwal and Rao, 1996). As such, it bundles attributes that provide satisfaction and benefits to the consumer.

Brand assets have been widely discussed in the literature, and researchers have proposed several ways to conceptualize, measure, manage, and enhance them. Researchers do not agree on a common perspective for studying brand assets. Instead, they have either used an individual consumer-oriented approach or a firm-level approach (e.g., Farquhar, 1989; Goldfarb *et al.*, 2007). As Ailawadi *et al.* (2003, p. 1) state, "[T]he two perspectives are linked because firm-level outcomes, such as incremental volume, revenue, price commanded, cash flow, and profit, are the aggregated consequence of consumer-level effects, such as positive image, attitude, knowledge, and loyalty." The several definitions that have been developed have in common that brand assets refer to the difference between outcomes accruing to branded products and those accruing to unbranded products (Aaker, 1991; Ailawadi *et al.*, 2003; Goldfarb *et al.*, 2007). If the outcome is viewed at the individual consumer-oriented level, an appropriate variable to study brand assets would be the price premium of a product due to its brand. If outcome however is viewed at the firm-level, appropriate measures would be profits, sales or market valuation. The former perspective attempts to measure the strength of consumer attachment to a brand, and the latter perspective conceptualizes brands as assets at the firm-level. Brand assets can thus be studied through two measurable constructs (Wood, 2000): brand strength and brand value. Wood (2000) argues that researchers taking a consumer-oriented perspective analyze the strength of a brand while firm-oriented approaches seek to analyze its value. This implies a causal relationship since the brand strength, which influences consumer product choice, ultimately materializes in brand value. Marketing activities such as advertising lead to brand strength and shape consumers' willingness to buy branded products (Farquhar, 1989). In turn, brand value as a financial measure ultimately depends on these strengths (Goldfarb *et al.*, 2007; Srivastava *et al.*, 1998). Since trademarks protect brands, brand management activities are mirrored in trademark portfolios. I thus argue that brand values, which are implicitly considered in company values, are reflected in the configurations of companies' trademark portfolios.

According to consumer-based approaches to study brand assets, consumers and their reactions to a company's marketing efforts are the main source of a brand's strength. Pitta and Katsanis (1995) found that brand strength is related to the probability of consumer choice and that brand strength leads to a higher degree of loyalty that "insulates the brand from a measure of competitive threats" (p. 56). The finding that brands affect consumer choice was confirmed by others (Agarwal and Rao, 1996; Srinivasan *et al.*, 2005). Brand strength can also be assessed by the price premia that branded products yield over unbranded products (Farquhar, 1989). Arvidsson (2006) argues that the strength of a brand resides in the minds of consumers. Interestingly, he argues that when trademark law protects brands from dilution, this body of law actually seeks to inhibit any interference with consumer perceptions. He concludes that what finally is protected is the "property over a specific share of mind" (p. 189). Similarly, Aaker (1991) suggests that a change in the brand's sign or name – which regularly are trademarks – might affect brand value. The main drivers of brand strength are awareness, loyalty, quality perception, associations, and other proprietary assets such as trademarks (Aaker, 1991; Seetharaman *et al.*, 2001; Srinivasan *et al.*, 2005). However, consumer-oriented approaches do not reveal the financial value of brand assets at the firm-level.

Firm-oriented approaches to study brand assets seek to analyze the financial value of brands. The financial value of a brand stems from its potential to generate future cash flows (Aaker and Jacobson, 1994; Goldfarb *et al.*, 2007; Srinivasan *et al.*, 2005). The two main sources of these cash flows – and, accordingly, the two main sources of brand value – are the brand's potential to increase the success of existing products and the brand's potential to successfully support launching new products (Smith and Park, 1992). Concerning existing products, future cash flows arise when price premia can be charged, when consumers are loyal, or when new consumers can be attracted. Cash flows from launching new products appear when the company decides to re-use an established brand to introduce new products. This popular strategy of line extension or brand extension will be described in greater detail below. Research has confirmed that stock markets consider brands in their firm valuations (Kallapur and Kwan, 2004; Lane and Jacobson, 1995; Simon and Sullivan, 1993). The estimation of the financial value of brands has been the subject of many research projects (e.g., Barth *et al.*, 1998; Kamakura and Russell, 1993; Keller and Aaker, 1992; Reddy *et al.*, 1994; Swait *et al.*, 1993). These studies acknowledge the importance of brands as intangible assets for a company.

In this study, I take a firm-oriented approach and estimate the financial value of brand assets through firm values in financial markets. According to Simon and Sullivan (1993, p. 29) brand assets originate from "the incremental cash flows which accrue to branded products over and above the cash flows which would result from the sale of unbranded products." Company communication and advertising, reflected in trademark portfolios, create brand associations for consumers (Aaker, 1991), thereby affecting their purchasing decisions leading to future cash flows (Goldfarb *et al.*, 2007). These are assessed by financial markets and materialize in companies' valuations in stock markets. However, since the market value of a firm in financial markets provides an "unbiased estimate of the future cash flows that are attributable to *all* of the firm's assets"[67] (Simon and Sullivan, 1993, p. 29), the value of a company's brand assets needs to be extracted. Simon and Sullivan (1993) employ such a methodology and show that brand assets are associated with companies' marketing decisions such as advertising expenditures or product introductions.

Clearly, the relationship between a company's products and its brands depends on the corporate brand strategy, the brand portfolio, and the trademark portfolio that is associated with the brand portfolio. Companies offering electronic products such as home entertainment systems (e.g., *Samsung*) or computer equipment (e.g., *Hewlett-*

[67] Emphasis added.

Packard) tend to use one strong brand that comprises large fractions of the company's total business. Other companies selling consumer goods (e.g., *Procter & Gamble*) follow a different strategy and create separate brands for each product or each product category.[68] Rao *et al.* (2004) link these brand strategies with company values in financial markets.[69] They argue that brand strategies can be plotted on a continuum with companies having a dominant corporate brand (e.g., *Samsung*, *Hewlett-Packard*) at the one end, and companies using several individual brand names with no corporate identification (e.g., *Procter & Gamble*) being at the other end. They find that corporate branding strategy is more highly valued in financial markets as compared to other branding strategies. They explain this finding through the differences in costs and benefits of these strategies. Having a strong corporate brand enables a company to concentrate on building and maintaining the reputation of a single brand, whereas a strategy of using an individual brand for each product requires a company to build a reputation for each of its brands. These differences affect future cash flows and, thus, the market value of a company.

4.2.2 Brand Management

The way in which brands and trademarks are managed is influenced by the branding strategy. Brand management deals with the management of the whole brand and trademark portfolio that a company owns. Although portfolios of brands have been considered in research (Aaker, 2004a; Montgomery and Wernerfelt, 1992; Petromilli *et al.*, 2002; Simmons *et al.*, 2000; Völckner and Sattler, 2006), this area lacks systematic examinations of brand portfolios and, in particular, trademark portfolios. Work in this area points out that, in addition to single brands, firms' entire brand portfolios are important to appropriately study companies that own multiple brands. Brand management involves marketing decisions that seek to build brand strength at the consumer-level. Moreover, companies are able to foster brand strength by filing trademarks that enable consumer perceptions to center on a particular graphically protected sign, thereby establishing a link between the consumers and the company. Finally, companies protect the strength of a brand by taking legal actions against competing businesses that seek to take unfair advantage of a brand by filing confusingly similar trademarks.

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[68] For example, some of the brands *Procter & Gamble* owns are *Duracell*, *Gillette*, *Lenor*, *Ariel*, *Pampers*, and *Pantene*.

[69] Aaker (2004) also described various brand strategies which are similar to those of Rao *et al.* (2004).

As Simon and Sullivan (1993) point out, studying brand assets correctly and objectivly allows an evaluation of the long-run impact of marketing decisions. Such decisions concern the structure of both the brand and the trademark portfolio. The structure of a brand or trademark portfolio can be regarded as the visible 'facade' of a company. It represents the way in which a company organizes its brands, marks its products, and interacts with the market. Aaker (2004a) illustrates the portfolio configuration with several examples and classifies the brands in companies' portfolios according to their roles. According to him, a parent brand is located at the top of the hierarchy, e.g., the brand *Sony*. Then, by extending the parent brand into a new segment, a novel so-called subbrand may emerge, e.g., *Sony Walkman*.

Brand management will be reflected in companies' trademark portfolios. For example, the register of CTMs shows that *Microsoft*, according to its trademark filings, sought to create a new brand for its operating system *Windows*[70] since it did not explicitly link the trademark's name to the corporate name.[71] *Microsoft* continued this strategy with subsequent versions (e.g., *Windows XP*[72] and *Windows Mobile*[73]). This is different from its package of office applications sold under the brand *Microsoft Office*[74]. *Microsoft* explicitly links this software package to its corporate name.[75]

It is important to point out the linkages of brand management to new product development and subsequent market introduction. If a new product has been developed, several issues are important for its introduction to the market. The company has to decide whether it should create a new brand or use an existing brand to cover it. When creating a new brand, the name to be chosen is a complex issue. Schuiling and Moss (2004) illustrate these difficulties in the pharmaceutical industry. For example, the name of a new pharmaceutical product may be a chemical-derived name, a therapy name, referring to a use, an indication, or a newly invented name. If the company

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70 CTMs No. 79681, No. 327890, and No. 1691963.

71 Here, creating a new brand explicitely needs to be distinguished from a new product. Of course, the new product may carry both trademarks, *Microsoft* and *Windows*. However, the name of the new trademark is *Windows* and not *Microsoft Windows*.

72 CTM No. 2160810.

73 CTM No. 3423845.

74 CTMs No. 951459, No. 2157113, and No. 7138225.

75 *Microsoft* does not call this software package simply *Office*, *Office 2000*, or *Office XP*. Obviously, the trademark *Office* is devoid of distinctive character, and its filing would be rejected if it has not gained distinctiveness through use. Although not protected, *Microsoft* could still use the term *Office* for advertising its software suite, something which has not happened. While trademarks like *Office 2000* or *Office XP* are unlikely to be subject of a rejection, *Microsoft* still did not register these trademarks.

decides to use an existing name to cover the new product, it has to decide whether the existing brand is used without change to label the new product or if the existing brand is used through a modified name, which may trigger the filing of a new trademark. It has been stated that the corporate name itself is usually among the most important brands a company owns (Aaker, 2004b). As the history of well-known brands shows (e.g., *Shell* or *Lufthansa*), a brand needs to be modernized to continuously serve as an attractive platform for extensions and new product launches (Farquhar, 1989; Farquhar *et al.*, 1992).

Brand management thus deals with two main decision categories. The first category involves decisions to create new brands or to use existing ones when introducing new products. If an existing brand is used to accommodate the new product, the brand is said to be extended or stretched (Aaker, 1990; Cabral, 2000b). The second decision category is solely associated with applying an existing brand and concerns the way in which the brand is developed. In general, it must be decided whether existing brand names should be used without any change or whether they should be modified. Developing a brand might elevate the brand to the status of an umbrella brand. An umbrella brand is a brand that spans various products, product classes or business segments but still seeks to communicate a common value proposition (Erdem, 1998; Sullivan, 1990; Wernerfelt, 1988). For example, *Virgin* can be viewed as an umbrella brand covering retail business, an airline, a radio station, and other business segments. According to the founder of *Virgin*, Richard Branson, "Consumers understand that all the values that apply to one product – good service, style, quality, value and fair dealing – apply to the others" (*Time Magazine*, No. 26, June 1996, cited by Andersson, 2002). Of course, a common value proposition of such different product categories all carrying the same brand is not always given. Still, the example of *Virgin* illustrates the breadth an umbrella brand can take.

4.2.3 Creating Versus Developing Brands

Brand management first involves the creation of new brands and, second, the development and leveraging of established brands, for example, by extending pre-existing brands to new products. If companies introduce new products, the decision either to create a new brand or to use an existing one is influenced by cost-benefit analyses (Choi, 1998; Smith and Park, 1992) and by the availability of a suitable brand for further development (Choi, 1998; Osler, 2004). The share of new products that use an existing brand through extension has been estimated to range between 80% and 95%

of all new product introductions (Aaker, 1991; Kim and Sullivan, 1998; Rangaswamy *et al.*, 1993). An interesting example is the car manufacturer *Toyota* (Choi, 1998). For communication to the mass market, it used its corporate brand *Toyota*, which is linked to introductions of new cars like *Toyota Aygo*[76] or *Toyota Yaris*[77]. However, when Toyota introduced *Lexus*[78] as a new car category to target the premium market segment, it avoided any associations with the corporate brand *Toyota* when filing trademarks. Obviously, the question arises why *Toyota* intentionally connected its cars for the mass market with its corporate name but chose a new unrelated brand for its luxury cars. According to Choi (1998), this can be explained by *Toyata* entering a new market segment with different consumer preferences.

When extending an established brand to a new product, researchers distinguish between line extension and brand extension (Aaker and Keller, 1990; Ambler and Styles, 1997; Reddy *et al.*, 1994). Line extension refers to the application of an existing brand to a new product with the new product being in a category the brand is already known in. In other words, the existing brand is not extended to new product classes. Examples include the broad product portfolios of consumer electronics manufacturers like *Hewlett-Packard*, which uses its corporate brand for virtually all new products. Brand extension involves the application of an established brand to different product classes that are new to the brand. An example is *Canon*, which initially produced photographic cameras and later extended its brand to printers and photocopiers (Cabral, 2000b). Another example is *Honda*, which originally produced motorcycles but later extended its name to automobiles as well as lawn and garden power tools (Dacin and Smith, 1994).

Instead of using the term brand extension, as most researchers do, sometimes researchers prefer to say 'brand stretching' (e.g., Pepall and Richards, 2002) although both mean the same. Some researchers explicitly focus on brand extensions (e.g., Smith and Park, 1992; Sullivan, 1992), and others focus on line extensions (e.g., Reddy *et al.*, 1994). The main features of both extension modes such as informational leverage, transferable reputation, and spillover effects – described in the next section – apply to

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[76] CTM No. 3342227.

[77] CTM No. 726026.

[78] CTMs No. 24406 and No. 24919.

both variants of extensions.[79] It needs to be noted that, depending on the definition of how broad a product class is, the distinction between line and brand extensions blur. While both line extension and brand extension refer to the *process* of extending an existing brand to new products, the term umbrella brand refers to the *result* of several extension processes: An umbrella brand is a brand that covers a broad range of different products or product classes and, thus, is to a large extent a result of multiple extensions.

A cost-benefit analysis compares the attractiveness of brand development to that of brand creation (Choi, 1998). For firms extending their brands either within or beyond original product categories, several sources of costs and benefits have been revealed by researchers. According to Smith and Park (1990), firms that use brand extension have lower advertising expenses and thus exhibit a greater advertising efficiency. Tauber (1988) found that on average the cost of introduction of a new product via a brand extension amounts to 50 million US dollars, compared to 150 million US dollars when a product is introduced with a newly created brand. Brand extensions also have a positive impact on the market share of new products (Smith and Park, 1992). Moreover, it has been stated that extensions have the potential to generate future cash flows and are valued by financial markets (Srivastava *et al.*, 1998). On the other hand, costs may be incurred if consumers become confused, for example, when a brand name is used on various products, leading to the dilution of the existing brand (Loken and John, 1993).

The availability of a suitable brand for development is required if a new product is to be introduced to the market by extending an existing brand (Osler, 2004). Obviously, if the company is not able to find leveragable associations with an existing brand, a new brand needs to be created. The suitability of developing a brand has been widely discussed in the marketing literature referring to the ‘fit’ between the parent brand and the extension (Aaker and Keller, 1990; Broniarczyk and Alba, 1994; Keller and Aaker, 1992; Reddy *et al.*, 1994; Völckner and Sattler, 2006, 2007). The parent brand could be damaged, for example, if two products carrying the same brand are too different leading to consumers’ confusion. In particular, quality considerations matter as the example of the brands *Toyota* and *Lexus* illustrated. Choi (1998) analyzed the decision of firms to use brand extension or to create a new brand and finds that “new brand

[79] For the remainder of this chapter, I will use ‘extension’ and ‘brand extension’ interchangeably, with ‘extension’ also covering ‘line extension’ if not noted otherwise.

names are created for high cost premium products such as *Lexus*, whose market is limited to upscale consumers"[80] (p. 666). His study focused on multi-product companies having different reputations in different markets. It has been found that the development of brands through extensions signals high quality; this will be described in more detail in the next section.

4.2.4 Informational Leverage, Transferable Reputation, and Spillover Effects

Extensions have been proven to be profitable strategies because of the reduced product introduction cost, the increased chance of success, the advertising efficiency that can be gained, the increased demand that an existing brand can provide to a new product, and the premium prices that can be charged (Aaker, 1990; Kapferer, 2004; Pepall and Richards, 2002; Reddy *et al.*, 1994; Smith and Park, 1992; Tauber, 1988). Any successful development of brands such as extending or modernizing brands would not be possible without informational leverage (Choi, 1998). Informational leverage builds upon transferable reputation and spillover effects between the parent brand and the new product. Spillover effects can also have a reciprocal nature since the brand value of the parent brand can in turn be enhanced or diminished (Swaminathan *et al.*, 2001). In all, it is important to also consider the extension potential of a brand when studying brand assets (Tauber, 1988).

Brand extension is a mechanism of informational leverage (Choi, 1998). Consumers make inferences from the performance of one product to other products using the same brand. For example, if a consumer discovers a product's inferiority, he might opt to not repurchase the same product again or refrain from purchasing another product that is affiliated with the same brand: The experience with his first purchase is valuable information regarding the second purchase. As Wernerfelt (1988) stated, consumers pool their experiences with several products and attribute them to the brand. Since consumers use these pooled experiences to infer the performance of other products of the same brand, the brand carries information, and companies can use the brand to transmit information to consumers. If companies extend an established brand to a new product, they seek to tap into consumers' experiences with products sold under the established brand and to link these experiences with the new product. Using informational leverage thus allows companies to alleviate the problem of asymmetric informa-

80 Emphasis added.

tion because consumers use the experience of old products to infer the performance of new products.

Companies can only solve the problem of asymmetric information through informational leverage if consumers correlate their beliefs about the quality of products sharing the same brand. This leads to spillovers from the experience of known products to unknown products. The assumption that consumers correlate their beliefs has been empirically validated using experimental settings (Aaker and Keller, 1990) and field data (Balachander and Ghose, 2003; Erdem, 1998; Sullivan, 1990). Aaker and Keller (1990) found that the perceived quality of one product provides a stock of information about the expected quality of other products. According to Erdem (1998), consumers' expectations about the quality of several products are highly correlated if these products share the same brand. The panel data that she uses in her regression framework concern dental care products of which some carry the same brand. Sullivan (1990) also uses field data from the automobile market and observes image spillovers. Hakenes and Peitz (2008b) point out that numerous product classes are concerned such as cars, consumer electronics, household durables, cosmetics, and many services (e.g., maintenance or financial services), since these product classes are characterized by imperfect observability of product quality.

The link between brand extension and product quality has been assessed in the economics literature. Extending brands to new products is a signal of high quality (Cabral, 2000b; Choi, 1998; Hakenes and Peitz, 2008b; Wernerfelt, 1988). Choi (1998) considers a multi-product monopolist introducing new experience goods.[81,82] He finds that informational leverage leads to less price distortion of the newly introduced products. According to him, firms stake their "reputation as a bond for quality in using brand extension as a signal of quality" (p. 655). Reputation is at stake if the association of a high-quality with a low-quality product adversely affects the profits of the former due to consumers' negative evaluation of the brand.[83] The reputation being transferred

[81] Experience goods require the consumer to first purchase the product before he is able to determine its quality (Nelson, 1970). Examples include appliances, automobiles, and consumer electronics.

[82] Choi (1998) argues that his model is complementary to the reputation model of Tadelis (1999). While the model of Choi (1998) focuses on inter-product transfers of reputation, Tadelis (1999) focuses on on inter-firm transfers of reputation.

[83] Choi (1998) states that brand extension is not the only mechanism for informational leverage. According to him, "any marketing arrangement that purposely associates one product with another" (p. 667) is a form of informational leverage as long as the company puts its reputation at stake. Hence, other mechanisms for informational leverage are sequencing of product introductions or bundling of products (Choi, 1996, 1998).

between products leads to both forward and reciprocal spillover effects (Wernerfelt, 1988). Wernerfelt (1988), using a signaling model, argues that a common brand shared by different products represents a 'performance bond' that only links high-quality products. The company's decision to extend a brand optimally spans only high-quality products in order to comply with consumer perceptions. If the company chooses to extend a high-quality brand to a low-quality product, it would jeopardize its reputation. Shirking on product quality by extending the brand to a low-quality product is thus prevented. The monopolist therefore uses brand extension only if the new introduced product is of high quality. Cabral (2000b) takes a different approach and compares high-quality with low-quality firms. He finds that high-quality firms whose reputation builds on past performance will often use extensions to transfer their reputation to new products. His model suggests that high-quality firms benefit more from reputation than low-quality firms. Thus, he argues that stretching reputation by means of extensions signals high quality. Hakenes and Peitz (2008b) argue that umbrella brands act as "a safeguard to consumers" (p. 547) and also provide incentives to companies to offer products of high quality if these products are sold under a well-developed brand. This is in line with the finding that umbrella brands act as full or partial substitutes to external quality certification (Hakenes and Peitz, 2008a). Moreover, Choi (1988) points out that brand extensions might enhance incentives for R&D.

Taking a broader perspective, Montgomery and Wernerfelt (1992, p. 50) argue that "reputational economies of scope" exist. This can be traced back to information spillovers, which exist between all products affiliated with one shared brand. If products are introduced sequentially, Smith and Park (1992) find that brand extensions benefit from spillover effects of the parent brand. However, it is important to note that both forward and reciprocal spillover effects exist (Balachander and Ghose, 2003). Balachander and Ghose (2003) apply scanner data from food products and find reciprocal spillover effects between products that carry the same brand, namely, that the success of the parent brand is affected by new product introductions carrying the same brand. These reciprocal spillover effects can be both negative and positive (Balachander and Ghose, 2003; Swaminathan *et al.*, 2001). Negative reciprocal spillovers exist because consumers might devalue the brand subsequent to an extension thereby also threatening other products affiliated with the brand. These negative reciprocal spillover effects can weaken the parent brand and can materialize through cannibalization or dilution of the brand (Aaker, 1990; Farquhar, 1989; Loken and John, 1993; Sullivan, 1990).

The success of extensions is mainly driven by the way consumers process information and evaluate the extension. The sources of success and failure of these instruments have been widely studied in the marketing literature (for a survey, see Völckner and Sattler, 2007). Some studies employed laboratory experiments and confronted potential consumers with hypothetical extensions (e.g., Aaker and Keller, 1990; Dacin and Smith, 1994) while others examined actual extensions (e.g., Erdem, 1998; Kim and Sullivan, 1998). The factors that drive extension success can be grouped into (i) determinants related to the parent brand, (ii) the relationship between the parent brand and the extension product, (iii) the extension's product class characteristics, and (iv) the characteristics of the company (Völckner and Sattler, 2007). Factors relating to the parent brand are the quality of the parent brand (Smith and Park, 1992), the associations with the parent brand (Aaker and Keller, 1990; Reddy *et al.*, 1994), the experience with a parent brand (Kim and Sullivan, 1998), and the brand's previous extension history (Dacin and Smith, 1994). In the second group, the most important factor is the 'fit' between the parent brand and the extension. The 'fit' usually involves the similarity or dissimilarity of the parent brand and the extension. To assess similarity, Aaker and Keller (1990) used the product classes of the original and the extension product. Numerous studies examined and confirmed the importance of this factor (Aaker and Keller, 1990; Broniarczyk and Alba, 1994; Keller and Aaker, 1992; Reddy *et al.*, 1994; Völckner and Sattler, 2006, 2007). The third group, which relates to characteristics of the extension's product class, covers factors such as the mode of product evaluation (i.e., search goods versus experience goods) (Smith and Park, 1992). Finally, the fourth group comprises company characteristics such as firm size or advertising support (Reddy *et al.*, 1994).

Having described the mechanisms that allow extensions to be a profitable strategy, I draw a broader picture in the next section to capture the full range of trademark filing strategies. I argue that extensions are an important driving force leading to new trademark filings. However, I will also point out other factors that lead companies to apply for trademarks. This broader picture describes why the development of brands, in which extensions play an important part, should be valued in financial markets.

4.2.5 Trademark Filing Strategies Reflecting Brand Management

From a brand management perspective, three trademark filing strategies exist: creating, modernizing, and extending brands. The fourth trademark filing strategy, hedging brands, cannot be derived from the perspective of brand management because the legal mechanisms of trademark law are its context.[84] While the first strategy concerns the creation of a new brand, the second and third strategy deals with the development of an existing brand. The second strategy aims at modernizing an already existing brand. This strategy corresponds to the renewal of an established brand to keep its appearance up-to-date and to maintain its strengths. The third strategy extends an established brand to a new product.

The creation of new brands may be required if the company wants to tap into new market segments and has no suitable brands to extend, as illustrated by *Toyota*'s creation of the brand *Lexus* (Choi, 1998). Such decisions are usually followed by the filing of trademarks. It has been shown that the introduction costs for products under a new brand are higher compared to the extension of pre-existing brands (Tauber, 1988). Moreover, the probability of success is lower if no backing from a reliable parent brand is available. I argue that financial investors have trouble to assess the future success of newly created brands. The difficulty of projecting the success of a new brand is illustrated by comparing this situation with the case where a brand extension is used. Then, investors can approximate the extension's future success based on the strength and history of the parent brand. If financial investors assess the potential of a new brand, they are confronted with greater difficulties when estimating future revenue streams.

Modernization of established brands can be viewed as the 'renovation' of existing brands. This strategy might be required to inhibit the dilution of a brand or to conserve a brand's potential to provide a platform for subsequent brand extensions. Situations in which a company uses this strategy include those where the brand's old appearance needs to be adjusted to a changing environment or those where a trademark needs to be altered to discard unwanted associations.[85] Practice shows that companies use this instrument regularly. Examples include *Shell*, whose corporate sign of a shell has undergone several changes, and *Lufthansa*, which redesigned both its corporate logo and its sign at various times. Actually, the modernization of established trademarks is linked to line extensions since an established brand is only modernized if the company seeks to use it for future products. However, I regard this strategy as a separate path

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[84] Each trademark only protects a single sign or word. Yet, a brand might need to be represented by a bundle of trademarks. This is addressed by the hedging strategy, which does not have its roots in brand management since it specifically builds on the nature of trademarks as IP rights and their relation to multi-faceted brands.

[85] Note that such situations involve the filing of new trademarks because registered trademarks generally cannot be altered (European Council, 1993, Art. 48).

for the development of brands since the main objective of this strategy is to keep the brand itself updated and renewed in order to uphold its strength, for example, to accommodate future extensions (Farquhar, 1989; Farquhar *et al.*, 1992). Although many well-known trademarks have undergone major and minor changes over time, this instrument has not been a major research issue. However, its existence is often implicitly assumed in the literature (e.g., Bass, 2004). As the product life cycle approach suggests, a product passes through different stages during its life cycle. It has been noted that brands need to be adjusted according to the stages of the branded products (Rajagopal and Sanchez, 2004). As with extensions, informational leverage increases the probability of successful product introductions. Moreover, only a strong brand can serve as the parent brand for future brand extensions (Smith and Park, 1992). Thus, I expect that modernizing brands as a trademark filing strategy is valued in financial markets.

Extensions are seen as beneficial because they reduce introduction costs for new products and increase the probability of product success (Aaker, 1990). They are profitable even if cannibalization between the parent brand and the extension brand is accounted for (Reddy *et al.*, 1994). Smith and Park (1992) found that advertising efficiencies can be realized and a greater market share can be captured through extensions. If both marketing expenses are lowered and revenues are increased through the use of extensions, future cash flows will rise. This is in line with Srivastava *et al.* (1998), who argue that extensions should enhance cash flows. As the market value of companies in financial markets represents the sum of all discounted future cash flows, extensions should be considered by investors in financial markets. Analyzing stock reactions subsequent to extension announcements, Lane and Jacobson (1995) confirmed that extensions can be financially beneficial, thus increasing the value of brand assets. When companies develop their brands by means of extensions, they file trademarks to protect these extensions. As illustrated with *Toyota* filing the trademarks *Toyota Aygo* and *Toyota Yaris*, trademarks allow us to observe extensions because they indicate the connection to the parent brand. Although the similarity of the parent brand and the extension is crucial to the success of extensions (Aaker and Keller, 1990; Broniarczyk and Alba, 1994; Keller and Aaker, 1992; Reddy *et al.*, 1994; Völckner and Sattler, 2006, 2007), companies often seek to launch products into unknown or rather distant product classes (Dawar and Anderson, 1994). Companies that employ extensions of this kind need to file new trademarks to gain protection in these new markets. Due to advertising efficiency, increased market growth, and a greater probability of success regarding new product introductions, I expect that extending brands as a trademark filing strategy is valued in financial markets.

To summarize, I argue that financial markets value those companies that employ trademark filing strategies which aim at developing and protecting established brands. This includes both fostering existing brands by means of modernization and disseminating established brands by means of extension. Financial markets should value the benefits of these strategies since they are likely to produce future cash flows. This is in line with other research which showed that stock markets consider brands in their firm valuations (e.g., Barth *et al.*, 1998; Simon and Sullivan, 1993). These brands obviously first need to be developed; and such brand development is mirrored in trademark filings. In order to connect these trademark filing strategies with companies' market values, the structure of corporate trademark portfolios first needs to be examined in detail. This is the objective of the next section.

4.3 Revealing the Structure of Trademark Portfolios

To assess trademark filing strategies and their valuation, the structure of how companies built their trademark portfolios needs to be known. Revealing the structure of trademark portfolios means that the various trademarks a firm possesses have to be grouped into separate coherent trademark families. I use the term 'trademark family' in order to denote a group of trademarks that jointly protects a brand to preserve its distinctiveness. This allows separating those trademarks potentially creating new brands from those that are filed adjacent to existing brands. For example, *Microsoft*'s brand *Windows* is protected not only by its corresponding trademark[86] but also by new trademarks that refer to the parent brand but have been filed subsequently such as *Windows XP*[87], *Windows Mobile*[88], or *Windows Vista*[89]. Trademark protection means that the distinctiveness of a brand can be maintained since trademarks allow their owners to take legal actions against counterfeiting, imitation, or competitors' filing of identical or confusingly similar trademarks (European Council, 1993, Art. 8, and Art. 9; Phillips, 2003). Thus, trademark families serve as the legal basis of a brand's distinctiveness and protect various facets and appearances of the brand. This section

[86] CTM No. 1691963.

[87] CTM No. 2160810.

[88] CTMs No. 3423845, and No. 3901527.

[89] CTM No. 4510749.

describes how these families are identified in trademark portfolios and which trademark filing strategies were employed by companies to form them.

First, I describe the source of the trademark data (Section 4.3.1). Then, I explain the consolidation of companies' trademark portfolios (Section 4.3.2). Drawing the border between companies is necessary for the third step, which presents the technique used to group a portfolio's trademarks into its families (Section 4.3.3). Finally, I use the revealed structures of the trademark portfolios to carve out companies' trademark filing strategies (Section 4.3.4). Since this is, to my knowledge, the first time that the structure of trademark portfolios is analyzed and that the connection between brands and trademarks is empirically examined, I present and explain the trademark portfolios of several companies in detail.

4.3.1 Data Source and Sample

For building corporate trademark portfolios, I used CTM data provided by the OHIM. This database represents a copy of the CTM register comprising all CTMs that have been filed between 1996 through 2004. There are no CTM filings before 1996 since the OHIM commenced its operations in that year. As this work analyzes trademark filing strategies, I argue that companies' branding aspirations, which materialize in these strategies, are best analyzed using trademark *applications*, regardless of whether an application is ultimately granted or rejected.[90] In all, the dataset from the OHIM comprises 402,724 trademark applications, of which 229,627 have been registered until the end of 2004 when the legal status of each application was recorded; 56,169 trademark applications failed, and 116,928 were still in the application process.

To group the trademarks within a company's portfolio into families, I rely on the relatedness between trademarks. Although trademarks "may consist of any signs capable of being represented graphically, particularly words, including personal names, designs, letters, numerals, the shape of goods or of their packaging" (European Council, 1993, Art. 4), I will focus on those trademarks that contain words or letters for two reasons. First, the relatedness between these text-based trademarks can be assessed more easily and more objectively than other types of trademarks such as pure graphical symbols, which would require a systematic examination of images. Second,

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[90] For the remainder of this chapter, the term 'trademark' is thus used to cover both applications and registered trademarks. This also applies to the terms 'trademark portfolio' and 'trademark families'.

the majority of trademarks are text-based, be it either a pure word mark or a trademark that includes text in its graphical depiction. Of all 402,724 trademarks in the dataset, 378,811 (94.1%) are text-based and analyzable.[91]

Companies of all sizes file trademarks. Applying the market value approach requires, however, that the companies are publicly listed. As in Chapter 3, I identified the world's largest publicly traded companies using the financial databases Reuters and Compustat. A total of 4,085 companies complied with my selection criterion of reporting at least 400 million Euros in revenues in their last income statement. Other criteria such as the selection of certain industries were not imposed. The next section describes how trademark portfolios were built for this set of companies.

4.3.2 Building Trademark Portfolios

To establish firm-level trademark portfolios, the trademarks of the OHIM database needed to be reconciled with the names of the 4,085 companies derived from the Reuters and Computstat databases. To consolidate trademarks at the corporate level, I employed the 'search engine logic' described in the appendix. This approach uses each company name as a search pattern and assigns the appropriate set of compatible trademark applicants to that company. This step is necessary since a company can be represented by multiple trademark applicants. There are three main reasons for this: First, spelling variations or misspellings can immediately lead to a seemingly inflated number of applicants.[92] Such variations of applicant names can be traced back to inconsistencies committed by the trademark applicant or the examiners at trademark offices. Second, a company changing its name or its legal form leads to multiple applicants. Third, a company as a corporate entity needs to be distinguished from trademark applicants as legal entities. From an organizational perspective, large corporations own different legal entities, which represent several divisions and departments. While financial statements are published on the corporate level, trademarks are filed on the level of legal entities. An appropriate consolidation of trademarks at the corporate level thus requires that all trademark filings of these associated applicants are pooled on the company-level. An examination of the data reveals that not all companies of the initial selection filed CTMs. Trademark applications were matched to 2,289 companies, which in total filed 57,370 trademarks with the OHIM. Table 19,

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[91] Actually, 383,495 trademarks are text-based but 4,684 of them cannot be systematically analyzed. Specifically, I declared those trademarks as analyzable which contained two or more alphanumeric characters.

[92] This issue has also been found to be a severe problem with patent filings (Magerman *et al.*, 2006).

discussed in detail in the next section, reports the top 30 companies as measured by the numbers of CTM applications they have filed (see the column containing the portfolio size). The Japanese company *Konami* tops the list, with 1,401 trademark applications, followed by *Procter & Gamble* (827 CTM applications) and *Deutsche Telekom* (797 CTM applications).[93]

4.3.3 Identifying Trademark Families

After building firm-level trademark portfolios, their structures are revealed. As pointed out above, I use the characters, words and syllables contained in trademarks to form trademark families within the portfolios. Within each corporate portfolio, trademarks are grouped into families by an iterative algorithm beginning with the first trademark filed and ending with the last.

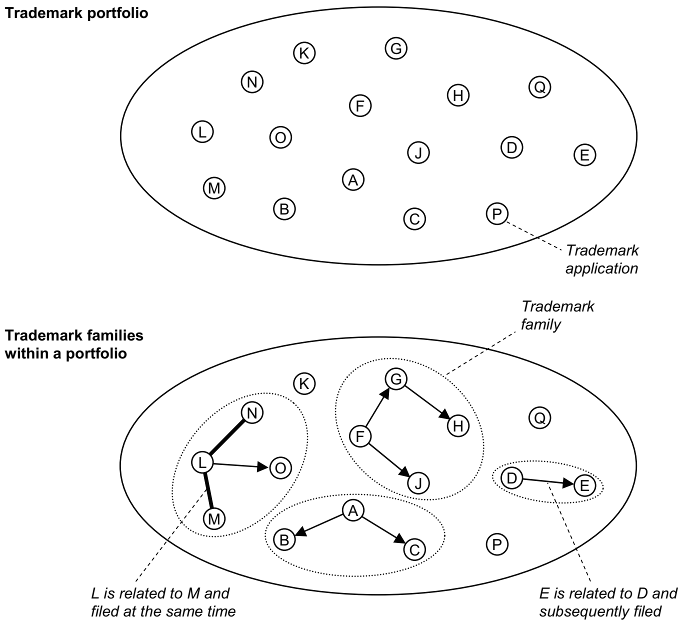
Based on this algorithm, the trademark families within a portfolio will be uncovered as illustrated in Figure 3. It begins with the first trademark filed by a company, trademark A, and gradually analyzes each trademark that is subsequently filed. As the second trademark B is filed by that company, the relatedness between both trademarks is assessed. If B is related to A, it is connected to the first trademark and creates a trademark family with two members. In Figure 3, this is indicated by an arrow. As the third trademark C is filed, the relatedness of this trademark to the preceding two trademarks, A and B, is assessed. Where the relatedness is greatest, trademark C is connected to that trademark, which is trademark A in Figure 3. As the fourth trademark D is filed by the company, its relatedness to all previous trademarks is assessed again. If it is found to be unrelated to any of the previously filed trademarks, it does not become connected to any preceding trademarks; instead, it becomes an independent trademark, at least until the new trademark E arrives. D and E are then connected because they show the highest relatedness compared to the other preceding filings. Note that trademarks K, P, and Q remain independent because they were not found to be related to others.

Depending on the highest relatedness to previous filings, new trademarks may also lead to ‘chains’ of trademarks. Figure 3 illustrates this by the trademarks F, G, and H. Trademark F, the first one filed within its group, initiated the trademark family. The subsequently filed trademark G was connected to F since G yielded the highest relat-

93 Note that 12 of these top 30 companies having the largest CTM portfolios are US-based. Companies' locations will be examined in more detail below when discussing the final dataset used in the market value regressions (Section 4.5.3).

edness. H was then filed and found to have the highest relatedness to G among all other preceding filings; hence, it is connected to trademark G and forms a ‘trademark chain’. This addresses the issue raised by Dacin and Smith (1994), who suggested that extension chains also need to be considered.

Figure 3: Trademark Portfolios and Trademark Families



The order of the algorithm explained above is determined by the filing dates of the trademarks. When multiple trademarks were filed on the same day, the CTM application numbers were used to order them simply because I assume that lower numbers are processed earlier by the OHIM than higher numbers. This may not be fully appropriate since companies might intentionally file multiple trademarks on the same day. Simultaneous filing is considered and accommodated in Figure 3 through the use of bold lines instead of arrows to represent such relations (trademarks L, M, and N).

The assessment of the relatedness among trademarks is a difficult issue. Every time a new filing enters the portfolio, the relatedness of this filing to all previously filed trademarks needs to be assessed pair by pair. When assessing these pairs, the pair showing the highest relatedness then needs to be figured out. If the similarity is below a certain threshold or if other criteria are not met, relatedness is rejected and no connection is created between the new filing and any of the previously filed trademarks. In this work, relatedness is based upon the text-based similarity of a trademark pair.[94] The similarity of trademarks can be analyzed solely on the basis of numerical string similarity algorithms like the Jaro-Winkler or the Levenshtein approach (Cohen *et al.*, 2003; von Graevenitz, 2007). Such algorithms provide a value that indicates the similarity estimate between any two strings. I use the bigram measure, whose values range between zero and one, with higher values indicating higher similarity. However, I found that trademarks contain specific words or syllables that have to be treated separately as it is these key terms that make up the reference to a common brand. For example, consider the filing of the trademarks *Roche*, *Roche Cardiac*, *La Roche*. The similarity metric of the bigram string comparator yields 0.89 for a comparison of *Roche* and *La Roche*. As I use a threshold of 0.7, this value is above the threshold indicating a reasonable degree of relatedness. However, although *Roche* and *Roche Cardiac* are also clearly related, the bigram metric indicates a similarity measure of 0.14, which mistakenly indicates a very low degree of relatedness.[95] Companies often seek to trigger spillovers from one trademark to another by intentionally making them similar or using common words or syllables in both. Hence, based on the construction of trademarks, a two-step approach is more appropriate when assessing their relatedness. In the first step, similarity is assessed based on words or syllables that are contained in both trademarks of each pair. In this step, for example, the fact that *Roche* is included in *Roche Cardiac* is considered as an indicator of high relatedness. The second step assesses similarity using the bigram string comparator as a similarity metric to assess imperfect string matches. In this step, the words a trademark is composed of do not matter. Instead, only the letters matter so that, for example, the trademark *Sulagil* can be found to be related to the trademark *Soulagil* although neither word is included in the other. I deem this hybrid approach of combining both seeking perfect matches and relying on similarity algorithms appropriate because it takes into account the way in which companies construct their trademarks to induce spillovers between them. Moreover, I expect that this approach – given that trademarks are compounds of words or syllables – is superior to applying solely numerical algorithms.

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[94] Specifically, only the alphanumeric characters of the texts contained in trademarks are used to determine the relatedness between trademarks.

[95] This is due to the algorithm that cannot distinguish between the relevant importance of the fragments *Roche* and *Cardiac*. Obviously, the former should be more strongly weighted, which my approach exactly seeks to do.

I apply the bigram string comparator as a similarity algorithm only in the second step. In the first step, however, *Roche* and *Roche Cardiac* are compared, and it is found that the text of the former trademark is fully included in the text of the latter trademark. Put differently, I argue that similarity within a pair of trademarks occurs in a hierarchy with five different layers. As different layers are given by the way in which trademarks have been constructed, the first step deals with determining the layer of each trademark pair. Higher layers represent higher degrees of relatedness. After the first step, pairs with lower degrees of relatedness are therefore ruled out and only the remaining pairs of the highest layer are passed on to the second step. To select the most similar pair in the second step, the bigram string comparator is then used.

In the first step, each pair is assigned to one of the following five layers whose explanation is organized in a descending degree of relatedness: The fifth layer, with the highest degree of relatedness, is used for trademark pairs where both trademarks are identical. The fourth layer regards pairs where one trademark as a separate word is fully included in the other one if and only if the other trademark begins with that word, e.g., *Roche* and *Roche Cardiac*. The third layer concerns pairs where one trademark as a separate word is fully included in the other one regardless of the position within the other trademark, e.g., *Panasonic* and *New Panasonic Special*. The second layer refers to those pairs where one trademark is fully included in the other one but not as a separated word, e.g., *Sanostol* and *Multisanostol*. The fifth layer does not require any common word or syllable but instead requires the bigram metric to be ≥ 0.7, e.g., *Sulagil* and *Soulagil* having a bigram metric of 0.97.

To illustrate the differences of this technique to others that seek to form groups in large networks, the total number of possible connections is an interesting criterion. On maximum, the technique used in this work establishes $n - 1$ connections given that the portfolio consists of n trademarks. Establishing trademark families through relatedness between trademarks aims at finding the preceding trademark that is most similar to the new incremental trademark entering the portfolio. New trademarks are therefore either connected to exactly one preceding trademark or connected not at all.[96]

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[96] This approach only produces robust results, however, if the relatedness observed within pairs of trademarks is unambiguous. If the assessment was ambiguous, one subsequent trademark would have to be linked to two or more preceding ones. The two-step approach of assessing relatedness outlined above turned out to have this characteristic: In all, 14,514 assessments of relatedness were performed, and the approach proposed potential 14,545 connections between trademarks. The difference between proposed connections and performed assessments is due to 31 assessments that had ambiguous outcomes as some incremental trademarks were proposed to be connected to two or more preceding trademarks because the bigram metric of the second

This is in contrast to other approaches that seek to find clusters in networks by connecting each node with multiple other nodes. Approaches of this kind would result in a maximum of $n(n-1)/2$ connections.[97] Because only very few studies dealt with trademarks and their portfolios, I preferred to use the technique described above due to its clarity and its replicability. Other approaches would add substantial complexity but would not greatly alter the outcome. Moreover, regarding trademark filing strategies, the approach used here complies with the suggestions set out by several researchers to systematically assess order, directions, and chains of extensions (Dacin and Smith, 1994; Dawar and Anderson, 1994).

To summarize the technique of identifying trademark families used in this work, new trademarks flowing into the portfolio are compared to all previously filed trademarks. This process leads to new trademark families, the growth of existing families, as well as a number of independent trademarks, which are not connected to any preceding trademark. A trademark family is thus defined as comprising at least two trademarks.[98]

After the last trademark has entered the portfolio, the outcome stage can be inspected. Figure 4 presents the trademark families in the portfolio of the telecommunications company *Vodafone*.[99] In all, *Vodafone* filed 53 CTM applications. Of these, 19 applications were independent and 34 applications were grouped in three trademark families. Note that Figure 4 only includes the trademarks arranged in families. As this figure shows, the largest trademark family agglomerates around the trademark *Vodafone*. This trademark family consists of 30 trademark applications. Each of the other two trademark families (*Intercare* and *Omnifin*/*Omniafin*) accommodates two applications. As arrows indicate successive filings and bold lines multiple filings on the same day, the development of this brand can be assessed.[100] Various subsequent filings made explicit reference to the trademark *Vodafone*. Some of these clearly extended the

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step did not produce unique values among the pairs. The trademarks involved in this rather low amount of uncertain assessments (i.e., the share of ambiguous connections is 0.2% of all assessments) were therefore randomly connected to one of the proposed preceding trademarks.

97 If all pairwise combinations of, for example, four objects A, B, C, and D are formed, six assessments (= $4 \cdot 3 / 2$) are required: A and B, A and C, A and D, B and C, B and D, as well as C and D.

98 Independent trademarks exist for several reasons, which are not distinguished in this study. For example, an independent trademark may singularly protect a brand or it protects a slogan in advertising. In both examples, the trademark is not related to others in the portfolio.

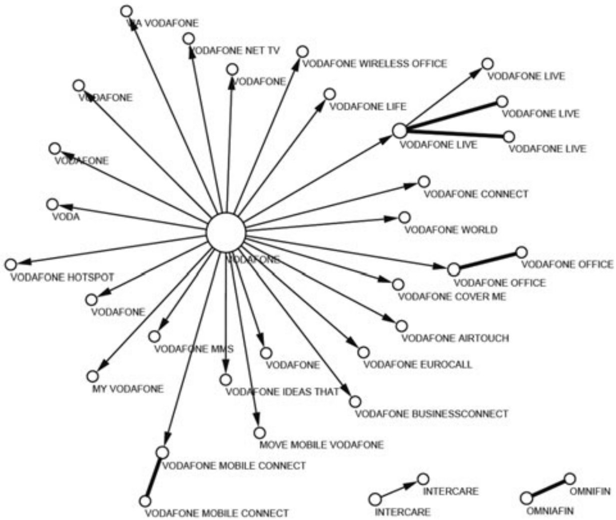
99 For graphically depicting the trademark families in this and the following figures, the program Cytoscape was used.

100 Note that the lengths of the connections vary only in order to display the trademarks in the best possible way. There is no additional interpretation of this.

parent trademark, e.g., *Vodafone Hotspot*. Others used the parent trademark without changing the text. This can be interpreted as modernizing or extending the parent trademark depending on the target product class of the new filing. *Vodafone Live* is also an interesting trademark. It clearly followed the parent trademark *Vodafone*. Instead of filing just one application, however, *Vodafone* filed four applications including the same text on the same day as indicated by the bold lines.[101] In all, this figure suggests that *Vodafone* has a rather developed umbrella brand.

Figure 4: Trademark Portfolio of *Vodafone*

(53 TMs in portfolio, thereof 34 TMs in 3 families. 19 independent TMs not displayed.)



[101] Three of these filings are figurative and differ in the way they are graphically represented. The fourth filing is a word mark.

Figure 5: Trademark Portfolio of *Microsoft*

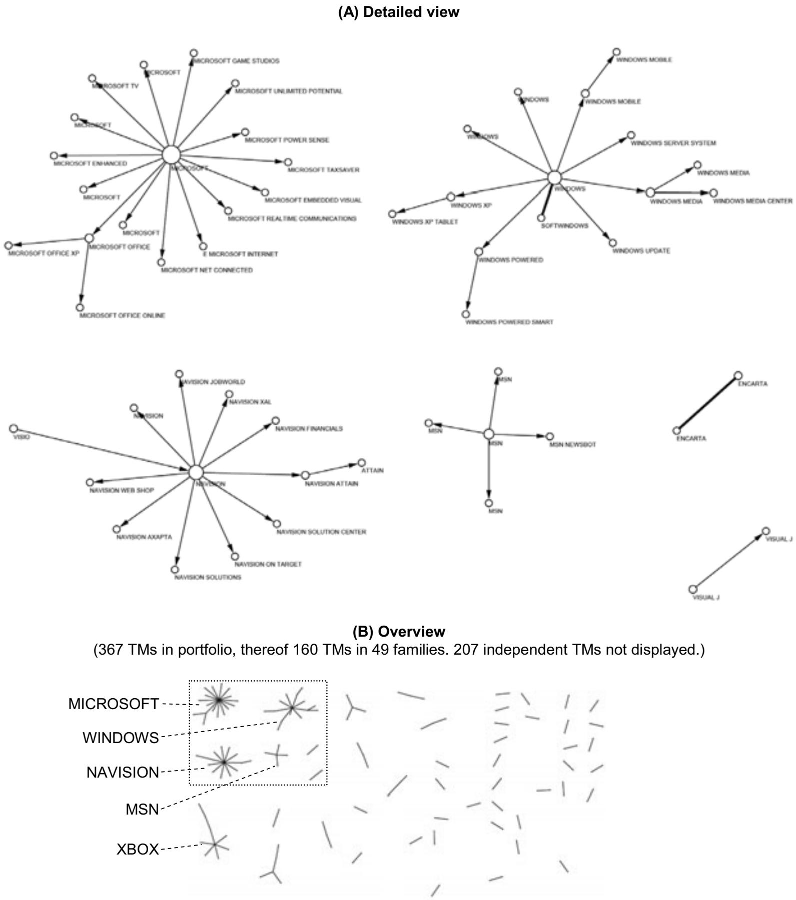


Figure 5 shows the trademark portfolio of *Microsoft*. In this figure, panel (A) shows a portion of the trademark portfolio in detail while panel (B) provides an overview perspective. I highlight this distinction as company portfolios are presented below which are too large to be shown in detail. *Microsoft* filed 367 trademark applications, of which 207 were independent and 160 were grouped into 49 families. This trademark portfolio shows that *Microsoft* has families of various sizes. Apparently, *Microsoft*'s corporate brand makes up the largest trademark family. Other large families are grouped around the operating system *Windows*, its enterprise resource planning software formerly known as *Navision* and its video game console *Xbox*. Figure 5 also shows how *Microsoft* filed trademarks both to create new brands and to further develop them through the filing of subsequent trademarks.

Figure 6 and Figure 7 show trademark portfolios of other companies in various industries: *Deutsche Telekom* operating in telecommunications, *BASF* producing chemicals, *Unilever* producing food and consumer goods, *Pfizer* operating in pharmaceuticals, and *Philips* mainly producing electronics.[102] The variety of trademark portfolios both in size and structure suggests that these companies employed different trademark filing strategies. Most companies developed certain larger core trademark families in addition to numerous smaller ones. With some companies, the corporate brand is protected by the largest trademark family in their portfolios (e.g., *Deutsche Telekom*[103], *Pfizer*, *Microsoft*, and *Vodafone*). With others, product-oriented brands are protected by more trademarks than the corporate brand (e.g., *BASF* and *Unilever*). Manufacturers of consumer goods such as *Unilever* rely on multiple strong brands applied to their products (Blichfeldt, 2005). A main reason for such fundamental differences in trademark portfolios are companies' business models and their industries, which lead them to emphasize different trademark filing strategies. Interestingly, the graphical depiction of *Philips*' trademark portfolio (see Figure 7) understates the number of applications *Philips* has filed. *Philips* filed 234 trademarks, of which only 20 are included in trademark families; the remaining 214 are independent applications. *Philips* files trademarks that are less related to each other than those filed by other companies like *Deutsche Telekom* or *Vodafone*. A reason might be that *Philips* uses its corporate brand to label its products and also new trademarks that are not associated with existing brands.

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[102] *Deutsche Telekom*, having one of the largest trademark portfolios, filed 797 trademark applications, of which 482 are contained in 137 families (see Figure 6). *BASF*, with 676 trademark applications, accommodates 174 of them in its 61 trademark families (see Figure 6). *Unilever*, having filed 348 trademarks, holds 193 applications in 53 families (see Figure 6). *Pfizer* filed 584 applications, of which 148 are included in 59 families (see Figure 7). *Philips* filed 234 applications, of which 34 are contained in 14 families (see Figure 7).

[103] The trademark family *Telekom* also includes all trademarks related to the corporate brand *Deutsche Telekom*.

Figure 6: Trademark Portfolios of *Deutsche Telekom*, *BASF*, and *Unilever*

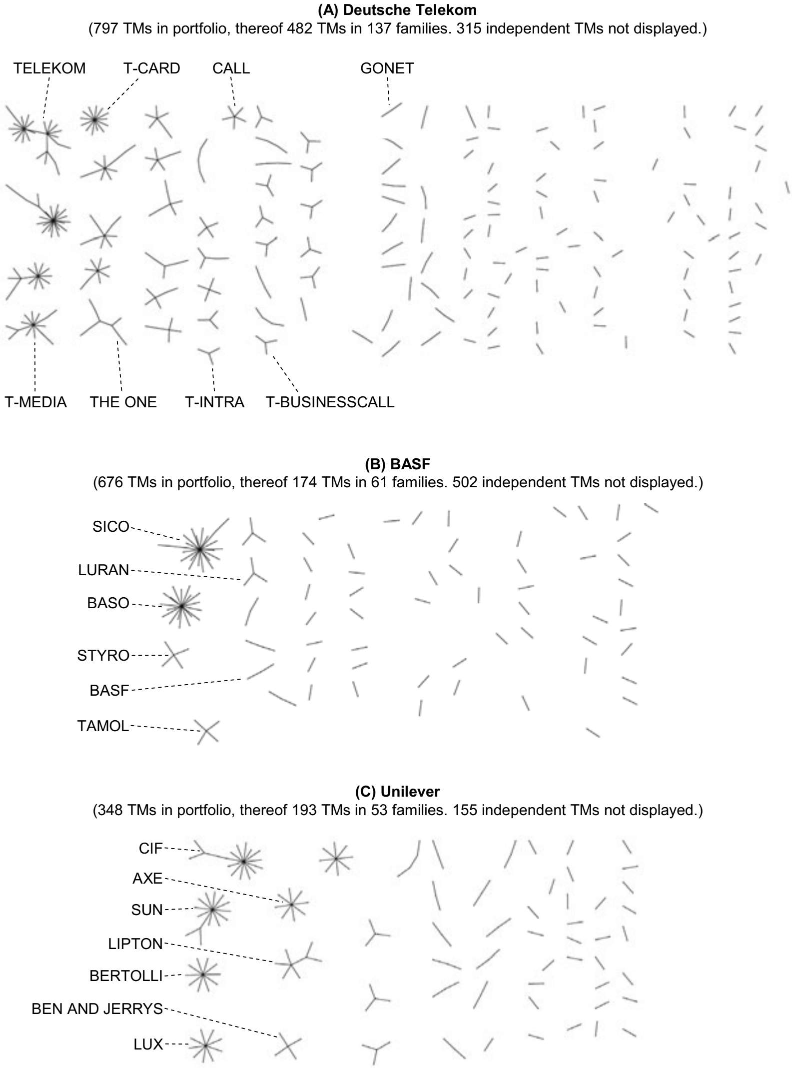
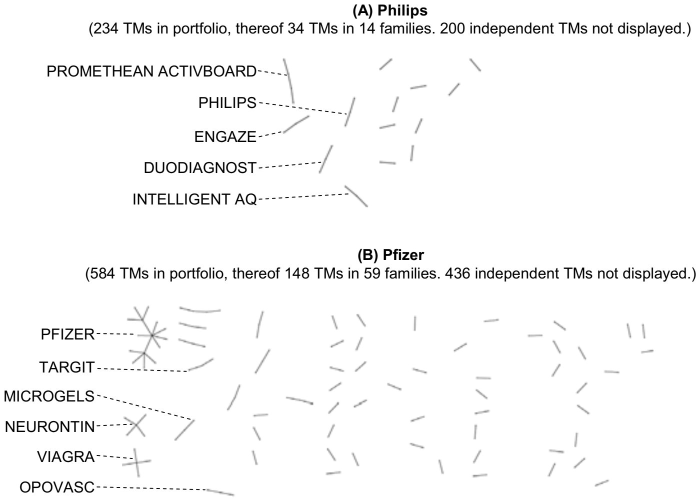


Figure 7: Trademark Portfolios of *Philips* and *Pfizer*



Both the order and direction of developing brands are important for corporate brand management (Dawar and Anderson, 1994). Families of various sizes as well as many independent trademarks emerge as a result of different brand management strategies. Table 17 shows how all 57,370 applications that were filed by 2,289 companies were grouped into families. 36,740 trademark applications (64%) were independent. The other 20,630 trademark applications (36%) were grouped into 6,146 families of varying sizes. About two thirds of the families consisted of only two trademark applications (13.8% of all trademark applications). Approximately one third of the families comprised 3 to 15 applications, representing 17.3% of all applications. 98 families had a size of 16 trademark applications or more, making up 4.8% of all applications.

I argue that brands are represented by trademark families. This is reasonable since the inclusion in a trademark family by the criteria used here requires inherent relatedness between the trademarks of a family. This relatedness allows consumers to transfer the reputation between products that may carry different but related trademarks. Companies thus intentionally use the relatedness of their trademark filings as the basis of informational leverage, which triggers spillover effects. Assuming that each product is sold under one main brand, these spillover effects mostly happen within the trademark family of that brand and are far less likely to happen between trademark families. This leads to another interesting interpretation of Table 17. It shows the distribution of the number of trademark applications on which companies build their brands. Trademarks form the legal basis for the differentiating power of brands (Phillips, 2003). Estimates of the number of 'legal roots' a brand might have, however, do not exist. Table 17 therefore provides some insights into the legal backing of brands.

Table 17: Distribution of Trademark Family Size

Family size	# of families	Located in these families	
		# of TMs	%
2	3,971	7,942	13.8%
3	923	2,769	4.8%
4	421	1,684	2.9%
5	232	1,160	2.0%
6-10	384	2,881	5.0%
11-15	117	1,477	2.6%
16-20	41	731	1.3%
21-30	32	791	1.4%
31-40	12	422	0.7%
41-50	6	262	0.5%
51-75	5	320	0.6%
75-100	2	191	0.3%
>100	0	0	0.0%
Families	6,146		
Trademarks in families		20,630	36.0%
Independent trademarks		36,740	64.0%
Total		57,370	100.0%

To provide further insights into companies' trademark families, Table 18 shows the 30 largest trademark families. It reports the family size, the company's portfolio size, and the share that this family takes in the portfolio. In the dataset, *MasterCard* holds the largest trademark family consisting of 99 trademark applications to protect the name of its credit card. The importance of this product to the company is highlighted by the share of 51.8% that this trademark family has in the company's total portfolio of 191 trademark applications. Another large trademark portfolio is owned by the car manufacturer *DaimlerChrysler*, which uses the word *Class* to name numerous car models. This trademark family comprises 92 applications and covers 12.3% of the total portfolio of 749 applications. Other large families are *Nissan* (68 applications representing 36.4% of the total portfolio), *Time* (67 applications, 33.3%), and *MTV* (66 applications, 21.5%). The share of the family in the total portfolio (i.e., the percentage values) is an interesting measure that highlights the importance of the family in the total portfolio. It also provides insights into the concentration of a company's trademark

Table 18: The 30 Largest Trademark Families

Rank	Name of trademark family	Family size	% of portfolio	Company	Country	Portfolio size
1.	MASTERCARD	99	51.8%	MasterCard Incorporated	US	191
2.	CLASS	92	12.3%	DaimlerChrysler AG	Germany	749
3.	NISSAN	68	36.4%	Nissan Motor Co., Ltd.	Japan	187
4.	TIME	67	33.3%	Time Warner Inc.	US	201
5.	MTV	66	21.5%	Viacom, Inc.	US	307
6.	SMIRNOFF	61	16.5%	Diageo plc	UK	369
7.	INTEL	58	64.4%	Intel Corp.	US	90
8.	DEUTSCHE POST	47	28.8%	Deutsche Post AG	Germany	163
9.	KLASSE	44	5.9%	DaimlerChrysler AG	Germany	749
10.	EMBRAER	44	34.9%	Embraer SA	Brazil	126
11.	PAMPERS	43	5.2%	The Procter & Gamble Company	US	827
12.	GAP	42	39.3%	The Gap Inc.	US	107
13.	COVISINT	42	16.4%	Ford Motor Company	US	256
14.	ESTEE LAUDER	40	28.2%	The Estee Lauder Companies Inc.	US	142
15.	SKY	40	81.6%	British Sky Broadcasting Group plc	UK	49
16.	HONDA	39	25.7%	Honda Motor Co., Ltd.	Japan	152
17.	UPS	36	46.2%	United Parcel Service, Inc.	US	78
18.	FORD	35	13.7%	Ford Motor Company	US	256
19.	PEPSI	35	17.4%	PepsiCo, Inc.	US	201
20.	AVON	34	42.5%	Avon Products, Inc.	US	80
21.	QUAM	33	30.6%	Telefonica SA	Spain	108
22.	PALMOLIVE	33	25.6%	Colgate-Palmolive Company	US	129
23.	UPM	33	75.0%	UPM-Kymmene Corp.	Finland	44
24.	FUJIFILM	32	16.8%	Fujifilm Holdings Corp.	Japan	191
25.	VIRGIN	32	39.0%	Virgin Media Inc.	US	82
26.	NIVEA	30	20.1%	Beiersdorf AG	Germany	149
27.	COLGATE	30	23.3%	Colgate-Palmolive Company	US	129
28.	VODAFONE	30	56.6%	Vodafone Group plc	UK	53
29.	PANTENE	28	3.4%	The Procter & Gamble Company	US	827
30.	SHELL	27	13.6%	Royal Dutch Shell plc	Netherlands	198

portfolio.[104] Among the 30 largest trademark families, this percentage measure exhibits large variation. *Procter & Gamble*, for example, has two trademark families ranking among the top 30, *Pampers* (43 applications) and *Pantene* (28 applications). Despite the size of these families, their portfolio shares are rather low (5.2% and 3.4%). This is in contrast to *Intel*, whose trademark family protecting its corporate brand appears to have one of the highest percentage measures in Table 18. This also leads to another noteworthy insight. Like approximately two-thirds of the companies in Table 18, *Intel* also protects its corporate brand with a large trademark family. As the congruence between family name and company name indicates, only about one third of the families in Table 18 protect brands that are unrelated to their corporate name. This adds to the importance of corporate brands (Aaker, 2004b; Rao *et al.*, 2004). It is also consistent with the observation that the typical industrial brand is the name of the company (Webster and Keller, 2004).

Table 19 reports the 30 largest trademark portfolios along with some characteristics of the portfolio structures. *Konami*, a Japanese electronics manufacturer has the largest portfolio with 1,401 trademarks. *Procter & Gamble* (827 filings) and *Deutsche Telekom* (797 filings) have the second- and the third-largest portfolios. The number of total applications in the portfolio of company *i*, TM_i, can be split into trademarks of different types:

$$TM_i = TMI_i + TMC_i + TMD_i. \tag{15}$$

TMI_i is the number of independent trademark applications, which are not linked to a trademark family. TMC_i is the number of those trademark applications that initiate a particular trademark family and to which subsequent trademark applications are connected. Thus, I argue that they refer to the brand creation efforts of a company. Finally, TMD_i is the number of applications that enlarge and develop existing trademark families. Therefore, I argue that these trademark filings reflect a company's brand development efforts.

[104] Note that this measure is not to be interpreted as the concentration or the distribution of a company's sales or its business activities.

Table 19: The 30 Companies with the Largest Trademark Portfolios

					Brand-creating TMs (TMC_i); # of families including …				Brand-developing TMs (TMD_i)	
Rank	Company	Country	Portfolio size (TM_i)	Inde-pendent TMs (TMI_i)	2-5 TMs	6-15 TMs	16-25 TMs	>25 TMs	# of TMs	%
1.	Konami Corp.	Japan	1,401	1,042	135	5	0	0	219	15.6%
2.	The Procter & Gamble Company	US	827	357	85	18	0	2	365	44.1%
3.	Deutsche Telekom AG	Germany	797	315	121	14	2	0	345	43.3%
4.	DaimlerChrysler AG	Germany	749	358	44	11	2	2	332	44.3%
5.	BASF SE	Germany	676	502	59	0	2	0	113	16.7%
6.	Sony Corp.	Japan	623	363	76	7	1	0	176	28.3%
7.	GlaxoSmithKline plc	UK	617	395	81	3	0	0	138	22.4%
8.	L'Oréal	France	592	452	42	1	1	0	96	16.2%
9.	Pfizer Inc.	US	584	436	58	1	0	0	89	15.2%
10.	Novartis AG	Switzerland	559	400	61	0	0	0	98	17.5%
11.	General Electric Company	US	474	380	34	2	0	0	58	12.2%
12.	Syngenta AG	Switzerland	430	312	49	2	0	0	67	15.6%
13.	International Business Machines Corp.	US	394	265	32	5	0	0	92	23.4%
14.	Diageo plc	UK	369	146	42	4	1	1	175	47.4%
15.	Microsoft Corp.	US	367	207	45	3	1	0	111	30.2%
16.	Bristol Myers Squibb Co.	US	358	232	48	1	0	0	77	21.5%
17.	Unilever NV	Netherlands	348	155	46	6	1	0	140	40.2%
18.	Altana AG	Germany	313	228	29	2	0	0	54	17.3%
19.	Hewlett-Packard Company	US	309	192	44	2	0	0	71	23.0%
20.	Viacom, Inc.	US	307	138	37	2	0	1	129	42.0%
21.	Volkswagen AG	Germany	292	178	33	0	0	1	80	27.4%
22.	Schering-Plough Corp.	US	291	221	23	1	0	0	46	15.8%
23.	Bayer AG	Germany	282	222	25	1	0	0	34	12.1%
24.	AstraZeneca plc	UK	280	203	24	2	0	0	51	18.2%
25.	Abbott Laboratories	US	278	184	33	2	0	0	59	21.2%
26.	Saint-Gobain SA	France	272	206	24	1	0	0	41	15.1%
27.	Sanofi-Aventis SA	France	271	201	25	2	0	0	43	15.9%
28.	Eli Lilly & Co.	US	270	139	39	4	0	0	88	32.6%
29.	Medtronic, Inc.	US	263	174	30	0	1	0	58	22.1%
30.	Ford Motor Company	US	256	110	14	4	0	2	126	49.2%

Table 19 includes these portfolio characteristics. *Procter & Gamble*, for instance, filed 827 trademark applications (TM_i), of which 357 were independent (TMI_i). Of the remaining applications, 105 initiated trademark families (TMC_i) and 365 were filed to develop existing families (TMD_i). Note that Table 19 splits TMC_i into various classes. Of the 105 applications initiating trademark families, 85 have been developed to families with a size of two to five trademark applications. 18 of those family-initiating trademarks subsequently developed into families with 6 to 15 applications, and two of these trademarks initiated families with more than 25 applications.

As the trademarks that a company filed can be differentiated according to their roles, Table 19 leads to some initial insights into companies' trademark filing strategies. Still, a thorough assessment of these strategies is not possible without a more detailed categorization of the role trademarks take within their family. The next section goes further in this direction in that it thoroughly reveals the trademark filing strategies that formed the families which were identified in this section.

4.3.4 Trademark Filing Strategies

The development of trademark families discussed in the previous section did not reveal how the development of the families proceeded. The way in which these families were developed depends on the particular filing strategies employed. In order to discriminate between these strategies, different roles of trademarks need to be identified. To examine companies' trademark filing strategies, it is therefore important to assess the role of each trademark application.

To distinguish between various trademark roles that develop existing brands, I draw on the characteristics that the connection between two trademarks exhibits. Based on these characteristics, for example, the 'fit' of the extension can be explored, which has been found to be an important factor (e.g., Aaker and Keller, 1990; Keller and Aaker, 1992; Reddy *et al.*, 1994; Smith and Park, 1992; Völckner and Sattler, 2006, 2007). To characterize the connection between two trademarks, I employ two dimensions: the linkage dimension and the market coverage dimension. The linkage dimension concerns the connection between two trademarks in a family, including similarity and filing sequence. The market coverage dimension comprises the congruence of the product classes covered by each trademark. Figure 8 summarizes the roles that a newly filed trademark can take in the portfolio. Note that the linkage dimension and the market coverage dimension are not mutually exclusive. Each trademark developing a brand takes two characteristics informing about its role: The first characteristic is given by the linkage dimension, the second by the market coverage dimension.

Figure 8: Trademark Roles

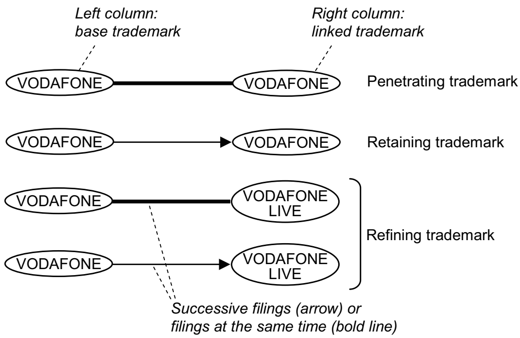
The linkage dimension concerns the connection between two trademark applications. This dimension is based on two factors. The first factor, filing sequence, refers to the elapsed duration between both applications. This distinguishes between trademark filings that were brought to the OHIM on the same day and those that were filed successively. The second factor is related to the content of both trademarks and refers to the degree of trademark similarity. This allows discriminating between a trademark 'update', where the texts of both trademarks are identical, and a trademark extension, which refers to a slightly altered trademark text (e.g., *Vodafone* and *Vodafone Live*).

The process of determining the linkage dimension and deriving a specific trademark role is illustrated in Figure 9. Recall that a bold line represents simultaneous filings and an arrow reflects successive filings. I argue that the linkage dimension reveals three roles that a developing trademark can take. For the purpose of this study, these roles were named as follows: First, the linked trademark can take the role of a *penetrating trademark* if both trademarks are filed on the same day and, additionally, the texts of both trademarks are equal.[105] Penetrating trademarks occur if a company seeks

[105] Note that equal texts do not necessarily imply equal trademarks, for example, if two similar logos or images include equal texts.

to protect very similar signs through multiple simultaneous filings. This might be necessary for strongly protecting a brand, for example, through multiple slight variations of the same logo containing equal content. Second, a trademark is a *retaining trademark* if it is filed subsequently and has the same content. For instance, trademark filings with equal content at different points of time are observed if a company redesigns its logo or otherwise updates it. Basically, retaining trademarks keep the content of an older trademark but adjust it or develop it further. Third, a *refining trademark* refers to trademarks in which the content is similar but not equal to a preceding one regardless of the duration between the two filings. A refining trademark uses the parent trademark and adjusts its content. This is typical for extensions where the parent brand is extended to a new brand to accommodate a new product introduction. Here, the new trademark is tailored for the new product but the new product is still put under the 'umbrella' of the parent brand. An example of this is *Toyota Yaris* and *Toyota*.

Figure 9: Linkage Dimension



The market coverage dimension relates to the congruence of the product classes of two connected trademarks. For example, if a brand is extended to a new product category, the company aims at leveraging its existing brands. New markets can be entered by applying an established brand to a new product. Researchers have highlighted the importance of the targeted product class and its relation to the product class of the parent brand in determining the success of such extensions (Dacin and Smith, 1994; Lane, 2000; Pepall and Richards, 2002).

With trademark data, the congruence between two successively filed trademark applications can be assessed according to the product classes to which each application is assigned. These product classes are set out by the Nice Classification and span 34 goods and 11 service classes (Mendonça *et al.*, 2004; WIPO, 2006). When filing a trademark, the applicant specifies the Nice classes in which he wishes to gain protection for. The applicant can choose any combination of Nice classes. He can even specify all 45 Nice classes.[106] However, the OHIM might reject this ambition and limit the Nice classes during the examination process (European Council, 1993, Art. 38).[107] Comparing the product classes affiliated with two connected trademarks allows one to measure the market-related congruence between both trademarks.[108] Assume that a trademark has been filed, for example, in the Nice classes 2, 3 and 4. This set of Nice classes makes up the benchmark against which a subsequent trademark filing is compared. If the subsequent trademark filing is, for example, affiliated with Nice classes 1 through 5, it is reasonable to argue that this subsequent filing is broadening the company's originally covered product classes (see Figure 10).

Comparing the overlap between the Nice classes of two trademarks leads to five different roles which, for the purpose of this study, were named as follows (see Figure 10). First, the subsequent filing can take the role of a *preserving trademark* if its set of Nice classes is identical to the preceding trademark. In this case, the market scope is not altered through the new trademark filing. Second, if the subsequent trademark application has only a subset of the Nice classes of the preceding trademark, it takes the role of a *narrowing trademark*. Here, the market scope decreases with the new filing. The third role is that of a *broadening trademark*, which includes additional product classes when compared to the preceding filing. Here, the market scope clearly increases. The fourth role is a *differentiating trademark*, which is affiliated with some of the preceding Nice classes but also adds new ones. Finally, the fifth role is a *diversifying trademark*, which has no Nice classes in common with its preceding trademark.

The approach described above helps to analyze the development of a company's brands, which might happen both within and beyond the original product classes. The market coverage dimension provides insights in which direction a company develops its brands.

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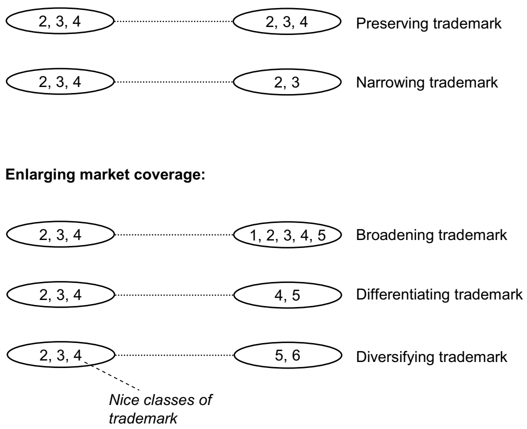
[106] The CTM No. 2977569 (*Nestlé*) is an example affiliated with all 45 Nice classes.

[107] A trademark might not be registrable for all kinds of goods and services. The trademark *Apple*, for example, is a generic term when applied to food and is thus not registrable in this product class. However, it is registrable for computers and consumer electronics because it is not generic for these products.

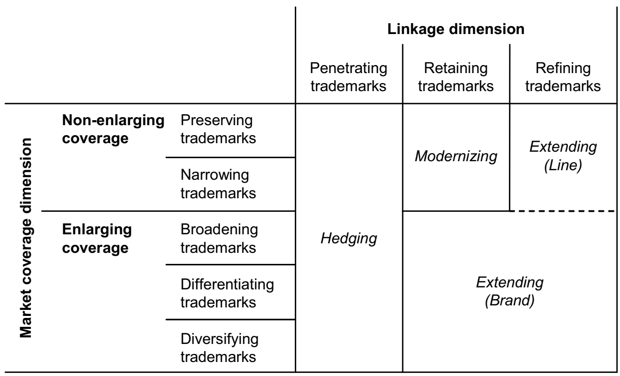
[108] Note that, due to revisions of the Nice Classification, only 42 classes could be considered until the end of 2001. Thereafter, 45 classes were considered (also discussed in Section 2.6.1).

Figure 10: Market Coverage Dimension



Both the linkage dimension and the market coverage dimension allow a characterization of those trademarks that develop brands. As the dimensions are not mutually exclusive, they can be combined as illustrated in Figure 11. More important, combining the linkage dimension with the market coverage dimension allows one to trace how companies develop brands through trademark filing strategies. Concerning the development of brands, I argue that the trademark filing strategies hedging, modernizing, and extending can be identified through these two dimensions.

Figure 11: Identifying Hedging, Modernizing, and Extending Strategies



Hedging as a trademark strategy has not yet been explained in this study. This strategy refers to the case where a company files multiple highly related trademark applications on the same day in order to strongly protect various facets of a brand. This strategy involves solely penetrating trademarks. What primarily distinguishes this strategy from the others is that here, simultaneous filings occur so that informational leverage is unlikely to be employed.

Modernizing as a trademark filing strategy is characterized by two conditions. First, the market scope is not broadened. Second, trademarks are filed gradually but still exhibit great similarities compared with preceding trademarks. This trademark filing strategy can be assessed based on those trademarks that take both the role of retaining trademarks and that of preserving or narrowing trademarks.

Extending as a trademark filing strategy can be identified in two ways. First, trademarks that are related but not identical indicate extensions. This includes examples like *Coke*, *Diet Coke*, and *Cherry Coke* (Aaker and Keller, 1990; Reddy *et al.*, 1994). Second, enlarging market coverage also represents extensions. This complies with the literature where entering new market segments is the key feature of brand extensions (Aaker and Keller, 1990; Reddy *et al.*, 1994). To accommodate both of these aspects, I argue that trademarks which enlarge the market coverage (broadening, differentiating, and diversifying trademarks) *and* which are filed subsequently (retaining and refining trademarks) reflect extending strategies. More specifically such a filing is likely to reflect a brand extension. However, trademarks that do not enlarge the market coverage (preserving and narrowing trademarks) can still reflect an extending strategy but only if the kind of linkages between the trademarks support it (refining trademarks). In this case, it is reasonable to assume that the filing reflects a line extension.[109]

Using this approach to categorize the trademarks in company portfolios allows studying to what extent companies employ different trademark filing strategies. Table 20 illustrates this decomposition not only for the total trademarks covered by the

[109] If the linkages between the trademarks suggest a high similarity (which means identical texts), the trademark filing strategy is however not extending but modernizing.

Table 20: Companies' Trademark Filing Strategies

	Total		Vodafone		Microsoft		Deutsche Telekom		BASF		Unilever		Philips		Pfizer	
	TMs	%	TMs	%	TMs	%	TMs	%	TMs	%	TMs	%	TMs	%	TMs	%
Trademark applications	57,370	100%	53	100%	367	100%	797	100%	676	100%	348	100%	234	100%	584	100%
Independent trademarks	36,740	64.0%	19	35.8%	207	56.4%	315	39.5%	502	74.3%	155	44.5%	200	85.5%	436	74.7%
Brand-creating trademarks	6,146	10.7%	3	5.7%	49	13.4%	137	17.2%	61	9.0%	53	15.2%	14	6.0%	59	10.1%
Brand-developing trademarks	14,484	25.2%	31	58.5%	111	30.2%	345	43.3%	113	16.7%	140	40.2%	20	8.5%	89	15.2%
Hedging trademarks	1,551	2.7%	4	7.5%	6	1.6%	60	7.5%	6	0.9%	2	0.6%	4	1.7%	10	1.7%
Modernizing trademarks	2,037	3.6%	1	1.9%	12	3.3%	20	2.5%	2	0.3%	18	5.2%	2	0.9%	20	3.4%
Preserving and retaining trademarks	1,525	2.7%	1	1.9%	7	1.9%	16	2.0%	1	0.1%	14	4.0%	2	0.9%	16	2.7%
Narrowing and retaining trademarks	512	0.9%	0	0.0%	5	1.4%	4	0.5%	1	0.1%	4	1.1%	0	0.0%	4	0.7%
Extending trademarks	10,896	19.0%	26	49.1%	93	25.3%	265	33.2%	105	15.5%	120	34.5%	14	6.0%	59	10.1%
Triggered by line extensions	5,555	9.7%	2	3.8%	28	7.6%	110	13.8%	65	9.6%	64	18.4%	10	4.3%	53	9.1%
Preserving and refining trademarks	3,638	6.3%	1	1.9%	15	4.1%	61	7.7%	51	7.5%	43	12.4%	10	4.3%	52	8.9%
Narrowing and refining trademarks	1,917	3.3%	1	1.9%	13	3.5%	49	6.1%	14	2.1%	21	6.0%	0	0.0%	1	0.2%
Triggered by brand extensions	5,341	9.3%	24	45.3%	65	17.7%	155	19.4%	40	5.9%	56	16.1%	4	1.7%	6	1.0%
Broadening and retaining trademarks	758	1.3%	4	7.5%	5	1.4%	18	2.3%	1	0.1%	17	4.9%	1	0.4%	3	0.5%
Broadening and refining trademarks	1,010	1.8%	5	9.4%	7	1.9%	48	6.0%	9	1.3%	15	4.3%	1	0.4%	0	0.0%
Differentiating and retaining trademarks	520	0.9%	2	3.8%	8	2.2%	5	0.6%	1	0.1%	1	0.3%	0	0.0%	0	0.0%
Differentiating and refining trademarks	1,133	2.0%	13	24.5%	14	3.8%	79	9.9%	3	0.4%	5	1.4%	0	0.0%	1	0.2%
Diversifying and retaining trademarks	1,101	1.9%	0	0.0%	21	5.7%	4	0.5%	0	0.0%	12	3.4%	1	0.4%	2	0.3%
Diversifying and refining trademarks	819	1.4%	0	0.0%	10	2.7%	1	0.1%	26	3.8%	6	1.7%	1	0.4%	0	0.0%

Table 21: Overview of Trademark Filing Strategies

Trademark filing strategy	Rationale	Measurement
Creating brands	– Protect newly created brands (e.g., for quality consistency reasons, new products or new product lines)	– Trademarks that initiate a family, which is subsequently developed by the filings of at least one other trademark
Hedging brands	– Protect different facets and appearances of a brand – Seek strong protection of a brand through filing of multiple slight variations of a sign	– Trademarks in families that (1) are filed on the same day as their connected trademark and (2) exhibit very similar trademark content as measured by identical texts
Modernizing brands	– Maintain the protection of an existing brand, whose trademarks need to be updated from time to time – Protect the differentiation potential of an existing brand – Conserve an existing brand as a powerful platform for future extensions	– Trademarks in families that (1) are filed subsequently to their connected trademark, (2) exhibit very similar trademark content, as measured by identical texts, and (3) do not enlarge the market coverage
Extending brands	– Extension as a mechanism of informational leverage since consumers correlate the expectations they have about products that carry the same brand – Use existing brand for launching new products in familiar (line extension) or new markets (brand extension) to raise advertising efficiencies and increase the success of new product introductions	– Trademarks in families that (1) are filed subsequently to their connected trademark, (2) exhibit very similar trademark content as measured by identical texts, and (3) enlarge the market coverage – Trademarks in families that (1) are filed subsequently to their connected trademark and (2) exhibit trademark content of lower similarity

companies in the sample but also for several corporate portfolios. 75.2%[110] of all trademarks that develop already existing brands can be traced back to extending strategies. Based on the categorization above, approximately half of these reflect line and half brand extensions (51% vs. 49%). Trademark filings based on hedging strategies have been employed nearly as frequently as modernizing strategies (10.7% vs. 14.1%). However, both hedging and modernizing strategies are less frequent than extension strategies.

Regarding the trademark filing strategies of specific companies, Table 20 shows that *Deutsche Telekom* to a substantial degree used hedging strategies to protect its brands: It rather frequently filed simultaneous applications for very similar trademarks. This is in contrast to *Unilever* which, to a large extent, used modernizing strategies. *Unilever*, like *Pfizer* and *BASF*, also engaged in trademark activities that preserved or narrowed its market scope. This is different from other companies such as *Vodafone*, *Microsoft*, or *Deutsche Telekom* which largely filed trademarks to broaden their market scopes.

110 Dividing the number of extending trademarks (10,896) by the number of brand-developing trademarks (14,484) yields 75.2%.

To summarize, the identification of trademark families allows scrutinizing how companies seek to protect their brands through trademark filings. This led to the distinction between trademarks that create brands and trademarks that develop brands. To examine more precisely the strategies companies employ to develop their brands, the trademarks were characterized according to their roles. In turn, the frequencies of these roles allowed determining which trademark filing strategies were employed by companies. Table 21 provides a summary of the four trademark filing strategies that have been identified: creating, hedging, modernizing, and extending brands. In the next section, I will present the market value approach and outline how the market value equation connects trademark filing strategies and company values.

4.4 The Market Value Approach

In this section, I explain the market value approach and present how other work has used this approach to measure the value contribution of intangible assets. I then describe how this model can be used to assess the valuation of different trademark filing strategies. Finally, I derive a form of the market value equation that can be empirically estimated using an NLLS regression framework. Despite some important differences, the approach is similar to the one used in Chapter 3.

The key characteristic of the market value approach is that it uses the market value of a company – observed in financial markets – as a forward-looking performance measure and relates it to both the tangible and the intangible assets a company owns (Hall, 2000; Hall and Oriani, 2006; Hall *et al.*, 2007). It seeks to assess the contribution of each asset class to the market value of a company. Using the market value of companies as a forward-looking performance measure builds upon the theoretical and empirical foundations of the efficient markets literature (Fama, 1970; Ross, 1983). Under the efficient market hypothesis, the stock price provides the best available unbiased estimate of the value of a company because it accurately reflects currently available information about future cash flows.

Basically, the market value approach assumes that the company is a bundle of both tangible and intangible assets that are treated symmetrically in the market value equation. The market value approach applies the idea of hedonic price models that seek to decompose the price of a good according to its characteristics. The price of a company is the company value derived from the price at which its stocks trade. As company characteristics, tangible assets and intangible assets are considered. The market value approach then allows one to estimate the relative contribution of several asset categories to the company value. To examine brand assets in this study, I use characteristics derived from companies' trademark portfolios. Since the way in which companies have built their brands is reflected in their trademark filing strategies, this allows an assessment of the contribution of different trademarks and their filing strategies to company values.

Tangible assets can be derived from companies' accounting data (Lindenberg and Ross, 1981; Montgomery and Wernerfelt, 1988). Yet, accounting struggles with the determination of the value of intangible assets (Lev, 2001). Researchers have still been able to estimate the value of intangible assets by relying on the market value approach. Hirschey and Weygandt (1985) found that both R&D and advertising expenditures are important factors in determining companies' market value although both are normally not reported as assets in the balance sheet.[111] Other research has confirmed that finding (e.g., Hall, 1993b). For example, accumulated R&D investments or patents have been used to assess the value of knowledge assets (Hall *et al.*, 2005; Hall *et al.*, 2007), and brand assets have been assessed employing measures derived from advertising expenditures (Connolly and Hirschey, 1988; Hall, 1993c; Hirschey and Weygandt, 1985; Villalonga, 2004) or trademarks (Bosworth and Rogers, 2001; Greenhalgh and Rogers, 2006a, 2006b). The market value approach assumes that a company is able to choose between different asset classes to invest in. Different tangible and intangible asset classes are treated additively and symmetrically in the market value equation (Hall and Oriani, 2006). A company may invest, for example, in intangible assets such as knowledge assets to develop innovative high-quality products, or it may invest in advertising to foster its brand assets.

Various studies have shown that brand assets are associated with the company value or its stock price (e.g., Barth *et al.*, 1998; Kallapur and Kwan, 2004; Lane and Jacobson, 1995; Rao *et al.*, 2004; Rao and Bharadwaj, 2008; Simon and Sullivan, 1993). There are two main linkages between brands and future cash flows that may influence investors' expectations (Smith and Park, 1992). The first linkage concerns the brand's contribution to the success of existing products. This, for example, includes cash flows generated from brand-related price premia, the loyalty of existing customers, or the

[111] Under particular conditions, R&D and advertising expenditures may be capitalized in balance sheets: If, for example, a company which has conducted R&D and advertising is acquired, its company value which also includes intangible assets can be capitalized in the balance sheet of the buying company.

potential to attract new customers. The second linkage refers to the potential of a brand to launch new products, meaning that revenue streams may originate from the extension of the brand to new products in both familiar and new markets.

Research has confirmed the contribution of different types of intangible assets to companies' market valuation. It is thus reasonable to consider both kinds of intangible assets: knowledge assets and brand assets. As set out in Equation 16, the market value equation assumes that the value of a company can be traced back to the sum of a company's different assets (Griliches, 1981). In other words, it is assumed that the company literally is the sum of its components. This results in

$$V_i(A_i, RD_i, ADV_i, TM_i) = q_i\left(A_i + \gamma_{RD} RD_i + \gamma_{ADV} ADV_i + \gamma_{TM} TM_i\right)^{\sigma} \quad (16)$$

with

$$q_i = \exp\left(c_k + m_l + u_i\right), \quad (17)$$

where V_i is the value of company i and A_i represents its physical assets. Knowledge assets are represented by RD_i, which are measured by a company's R&D investments (Hall, 1993b, 1993c; Hall and Oriani, 2006; Jaffe, 1986; Johnson and Pazderka, 1993). Brand assets are included through a company's advertising investments ADV_i and its trademark portfolio TM_i.[112] q_i is a valuation coefficient that includes an individual disturbance in the valuation, u_i, as well as overall valuation effects such as differences in valuations regarding country k, and industry l. These country- and industry-specific valuation effects are shown by c_k and m_l, respectively. As returns to scale are measured by σ, a value of unity indicates constant returns to scale. Values exceeding unity indicate economies of scale and values below unity diseconomies of scale.

Based on the marginal values γ, the contribution of the different asset classes to the company value can be derived both as relative shadow values referring to physical assets or as absolute shadow values referring to companies' market values (Hall, 1993c; Hall and Oriani, 2006). It is important to note that, since these shadow values are equilibrium outcomes in financial markets, they cannot be interpreted as structural parameters (Hall, 2000; Hall and Oriani, 2006). These values emerge as companies

[112] Note that RD_i and ADV_i are monetary measures and that TM_i reflects the portfolio size of the company's trademark portfolio. Note also that all three measures of intangible assets are stock variables (as opposed to flow variables). Thus, they do not only include the recent year, as would be the case with flow variables, but are also driven by previous years.

provide investment opportunities and investors evaluate these companies based on their future performance potential. Investors take action by buying or selling company shares so that the stock price as an aggregate measure changes and, with it, the market value of the company. Given that σ is unity, $q_i\gamma_{ADV}$ is the absolute shadow value of advertising investments. That is, it indicates how one additional unit invested in advertising contributes to the company value from the perspective of investors. γ_{ADV} is the relative shadow of one additional unit spent on advertising measured in terms of physical assets but it does not reflect investors' expectations. Analogously, $q_i\gamma_{TM}$ is the absolute shadow value of trademarks indicating the contribution of one trademark to the company value from an investor's perspective. Then, γ_{TM} is the relative shadow value of trademarks indicating the value of one trademark in terms of physical assets.

Having presented the market value equation on a general level, I now further develop this equation in order to arrive at a form that not only can be empirically estimated but also accommodates the characteristics of trademark portfolios as measures that reflect trademark filing strategies. Rewriting Equation 16 yields

$$\log\frac{V_i}{A_i} = \log q_i + (\sigma - 1)\log A_i + \sigma \log\left(1 + \gamma_{RD}\frac{RD_i}{A_i} + \gamma_{ADV}\frac{ADV_i}{A_i} + \gamma_{TM}\frac{TM_i}{A_i}\right). \quad (18)$$

Here, Tobin's q, the ratio of the market value of the company to the replacement cost of the company's assets, is represented by the fraction on the left side (Rao *et al.*, 2004). If the company value exceeds the value of its physical assets, Tobin's q is larger than one. Equation 18 clearly shows that, *ceteris paribus*, intangible assets as measured by their intensities regarding physical assets can lead to a markup over physical assets. Simon and Sullivan (1993), for example, use a similar approach to study brand assets.

In this work, I argue that the trademarks in a corporate portfolio have different roles and hence contribute differently to a company's market value. If trademarks in a corporate portfolio can be decomposed into several groups, the contribution of each group of trademarks to the company value can be assessed. Assuming that the trademarks of company i can be decomposed into s groups leads to:

$$TM_i = \sum_{j=1}^{s} TM_{i,j}\ . \quad (19)$$

This allows us to write Equation 18 as

$$\log\frac{V_i}{A_i} = \log q_i + (\sigma - 1)\log A_i +$$

$$\sigma \log\left(1 + \gamma_{RD}\frac{RD_i}{A_i} + \gamma_{ADV}\frac{ADV_i}{A_i} + \sum_{j=1}^{s}\gamma_{TM,j}\frac{TM_{j,i}}{A_i}\right). \tag{20}$$

With Equation 20, different decompositions can be used and compared. Then, based on their marginal values, the value contributions of different trademark types can be assessed. For example, trademarks that created brands can be compared to independent trademarks and to trademarks that developed already existing brands. I will draw upon the decomposition of the trademark portfolio shown by Equation 19 when estimating the market value equation. This allows assessing the relationship between trademarks that reflect different filing strategies and brand assets.

Another feature of Equation 20 is that it provides a functional form that can be empirically estimated using regression techniques. Early research that applied the market value approach used OLS regressions based on the approximation of *log*(1 + *x*) with *x*, which is only sufficiently accurate for small values of *x* (Cockburn and Griliches, 1988; Griliches, 1981; Jaffe, 1986). However, as NLLS regression techniques do not require this approximation, they are superior to OLS in cases where the functional form is non-linear as is the case with the market value equation. By specifying the functional form of the regression equation during the estimation process, NLLS allows the estimation of non-linear relationships between the dependent variable and the regressors. I follow preceding work and employ NLLS for estimating the market value equation (Hall *et al.*, 2005; Hall *et al.*, 2007). The next section describes the construction of the dataset used in the estimations.

4.5 Dataset, Variables, and Descriptive Statistics

In this section, I describe the dataset, used to estimate the model developed in the previous section. The final dataset includes accounting and financial data in addition to the characteristics derived from companies' trademark portfolios. I first explain how the final dataset is constructed (Section 4.5.1). Then I describe the variables that enter the empirical model (Section 4.5.2). Finally, I present descriptive statistics for the variables in the dataset (Section 4.5.3).

4.5.1 Dataset

Accounting and financial market data were taken from the Compustat database[113] and from the Reuters database. The Compustat database provided companies' market capitalizations, total assets, total debts, and R&D expenditures. Since this database did not contain companies' advertising expenses, I supplemented the data obtained from Compustat with the advertising expenses data from Reuters. The available trademark data from the OHIM included all trademark applications until the end of 2004. All trademark portfolio characteristics have been computed for that date. Due to the cross-sectional nature of the dataset, I obtained companies' market capitalization at the end of 2004 and took total assets and total debt as reported in companies' balance sheets of 2004. As accumulated R&D and advertising investments enter the market value equation, a reliable computation of these R&D and advertising stocks ideally requires full histories of annual R&D and advertising expenditures. Accordingly, all available R&D and advertising expenditures from the income statements of 2004 and earlier were obtained from Compustat and Reuters. To produce consistent Euro values, historical currency rates were applied. In addition, although it was only necessary to compute R&D and advertising stocks for 2004, the annual R&D and advertising expenditures used for the computation of stocks also included earlier years, requiring an inflation adjustment to arrive at consistent real 2004 prices.[114]

Corporate trademark portfolios could be built for 2,289 worldwide publicly listed companies in the sample drawn from Compustat and Reuters. Some of these observations, however, included missing values and outliers, so they were removed to arrive at a dataset that could be used for estimation. The exclusion of those observations that contained missing values reduced the dataset to 1,841 observations. This loss can be attributed to the computation of Tobin's q, which required the components total assets, total debt, and market capitalization. To identify outliers, the variables Tobin's q, the ratio of the trademark applications to assets, the ratio of the R&D stock to assets, and the ratio of the advertising stock to assets were considered. For each of these variables, the 1st and the 99th percentiles were computed. If one of the measures was outside the boundaries given by these percentiles, the observation was dropped. The resulting dataset comprised 1,735 observations.

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[113] The Compustat database is provided by *Standard & Poor's*. Precisely, the international data required in this study is offered by GlobalVantage, a license within Compustat.

[114] To do this, the GDP price deflator available in Ameco, an annual macro-economic database provided by the European Commission, was used. Specifically, the item *PVGD* was used and re-indexed to 2004.

4.5.2 Variables

Tobin's q, the dependent variable in the market value equation, is computed by using both accounting and financial measures since it is the ratio of the market value of the company, V, to the replacement costs of the company's assets, A (Rao *et al.*, 2004). For the replacement costs of the company's assets, its total assets are used as reported on its balance sheet. The market value of a company is the sum of the market capitalization, MC, and the market value of its debt, MD. However, as the market value of a company's debt is difficult to observe and estimate (DaDalt *et al.*, 2003; Hall and Oriani, 2006), it is usually proxied by the total debt as reported on the balance sheet.[115] Thus, Tobin's q is computed by adding up market capitalization and total debt (Compustat item *DT*) and dividing this sum by total assets (Compustat item *AT*). The market capitalization is the product of the number of outstanding shares (Compustat item *CSHO*) and the price at which a company's stock trades (Compustat item *PRCCM*). The computation of Tobin's q, regularly employed by other studies, is thus given by:

$$\frac{V}{A} = \frac{MC + MD}{A} \approx \frac{CSHO \cdot PRCCM + DT}{AT}. \tag{21}$$

Advertising and R&D investments are symmetrically computed: Even though some studies have simply employed annual R&D or advertising expenditures of the observation year (Greenhalgh and Rogers, 2006a; Simon and Sullivan, 1993), I follow other studies that sought to estimate R&D investments based on time series of annual expenditures (Hall *et al.*, 2005; Hall *et al.*, 2007). The reason for this is that intangibles such as knowledge assets or brand assets have usually not been produced only by the R&D and advertising expenditures of the year when the market value was recorded. Instead, intangible assets generally have accumulated over a longer period of time (Ross, 1983). However, these R&D and advertising investments are not capitalized in companies' balance sheets (Ross, 1983). Instead, such investments are largely treated as expenditures and they are reported on companies' income statements in the year of occurrence. Hence, in order to estimate knowledge assets, researchers have used histories of R&D expenditures as annual flow measures to compute R&D stocks. To do this, the so-called declining balance formula with a constant depreciation rate, δ, has regularly been used (e.g., Hall and Oriani, 2006; Hall *et al.*, 2005; Hall *et al.*,

[115] The total debt is the sum of long-term debt and debt in current liabilities.

2007).[116] This formula allows the computation of stock measures (RD_t and ADV_t) at time t based on past and present flows (RD_t^{flow} and ADV_t^{flow}). Following others, I apply a depreciation rate of 15%. Due to the depreciation rate, past expenditures will affect the stock less than present expenditures. This is reasonable, as technological knowledge becomes obsolete over time and brands need to be continually advertised to maintain their awareness. Thus, I compute R&D and advertising stocks analogously:[117]

$$RD_t = RD_t^{flow} + (1-\delta)RD_{t-1} \tag{22}$$

and

$$ADV_t = ADV_t^{flow} + (1-\delta)ADV_{t-1}\,. \tag{23}$$

Since infinite previous histories of expenditures demanded by Equations 22 and 23 are not available, the initial stock for the first available observation year of expenditures needs to be computed. Assuming that the expenditures have been growing at a constant annual rate, g, of 8% prior to the observed time series of expenditures allows a computation of these initial stocks:

$$RD_0 = \frac{1}{\delta + g} RD_0^{flow} \tag{24}$$

and

$$ADV_0 = \frac{1}{\delta + g} ADV_0^{flow}\,. \tag{25}$$

Not all companies report R&D or advertising expenditures. In some cases, companies do not perform any R&D or do not engage in advertising. In most countries, companies may choose whether or not to disclose their R&D and advertising expenditures (Hall and Oriani, 2006). The latter case needs to be addressed as companies' deliberate choice of disclosure might be strategically influenced, leading to biased estimates due to sample selection. However, Hall and Oriani (2006) empirically found that a company's decision to publish R&D expenditures induced no sample selection bias.

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116 For details regarding the declining balance formula see Hall (1990).

117 R&D expenditures were obtained from Compustat (item *XRD*) and advertising expenditures from Reuters (item *Advertising Expense*).

Following other work, two dummy variables will capture the non-availability of R&D and advertising stocks.[118]

The total number of trademark applications a company filed (i.e., the trademark stock) can be decomposed into different groups. Depending on the affiliation with trademark families, the trademarks in the total portfolio of company *i*, TM_i, can be divided into brand-creating trademarks, TMC_i, brand-developing trademarks, TMD_i, and independent trademarks, TMI_i:

$$TM_i = TMC_i + TMD_i + TMI_i\,. \tag{26}$$

By definition, TMC_i, the number of brand-creating trademarks, equals the number of trademark families. Interesting insights into a company's brand management can be gained if these brand-creating trademarks are split into those that initiate smaller families and those that initiate larger ones. As a cut-off value I use a family size of 15 applications, leading to brand-creating trademarks that induce smaller families of 15 trademarks or less, $TMF1_i$, and brand-creating trademarks that initiate larger families of 16 trademarks or more, $TMF2_i$. This decomposition is then given by:

$$TMC_i = TMF1_i + TMF2_i\,. \tag{27}$$

Brand-developing trademarks can be assigned to different filing strategies according to their roles, which are determined by the ways in which the trademarks are embedded in their families. Thus, TMD_i, the number of company *i*'s brand-developing trademarks, can be decomposed into hedging trademarks, $TMDH_i$, modernizing trademarks, $TMDM_i$, and extending trademarks, $TMDE_i$. Each addend reflects a company's emphasis on different developing strategies:

$$TMD_i = TMDH_i + TMDM_i + TMDE_i\,. \tag{28}$$

A company's extending trademarks, $TMDE_i$, can be further divided according to the mode of extension. Then, $TMDE_i$ is the sum of extending trademarks assumed to be triggered by line extensions, $TMDEL_i$, and those assumed to be triggered by brand extensions, $TMDEB_i$:

$$TMDE_i = TMDEL_i + TMDEB_i\,. \tag{29}$$

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118 Stocks will also be unavailable if the history of R&D or advertising expenditures is interrupted. That is because the declining balance formula requires histories of past and present flows to be continuous.

This decomposition provides insights into the different purposes for which trademarks are filed. When integrated into the market value equation, these decompositions allow an assessment of how different trademark roles are valued and which effects different filing strategies have.

Finally, control variables capture country- and industry-specific valuation effects. The industry classification of companies is based on SIC codes. Since no selection criteria regarding industry membership were imposed in the selection of the sample, I basically used the SIC division structure to categorize companies. The division structure provides a basic categorization (e.g., 'manufacturing', 'services', 'transportation, communications, and infrastructure', 'construction'). However, since there are many companies in manufacturing, it was further distinguished between different areas within manufacturing (e.g., 'food and kindred products', 'chemicals', 'transportation equipment', 'instruments for measuring, analyzing, and controlling'). Ultimately, this approach categorized the companies into 31 industries, of which the largest category held 11.7% of all observations ('transportation, communications, and infrastructure', see Table 23 discussed in the next section).

4.5.3 Descriptive Statistics

Descriptive statistics for the 1,735 observations in the dataset are reported in Table 22. Tobin's *q* is 1.2 on average. With values ranging from 0.26 to 4.83, a large variation in company performance exists. A Tobin's *q* value exceeding one indicates that the market value of a company as a measure of aggregate investor expectations is higher than its physical assets. One reason for this is that intangible assets also contribute to companies' market value. As Tobin's *q* is a compound of accounting and financial measures, its components reflect the size of the companies. On average, market capitalization is 6,236.8 million Euros. Debt on average is 2,480.8 million Euros. The mean value of total assets is 8,242.6 million Euros. As both the standard deviations and the ranges of these measures show, the size of the companies varies to a large degree. The smallest company exhibits total assets of only 53.3 million Euros while the largest company has assets of 552.4 billion Euros.

As R&D expenditures were not available for each company, R&D stocks could not be computed in 46.1% of all cases. For the remaining 935 companies, the average R&D stock is 1,523.1 million Euros. Advertising stocks could only be computed for 434 observations representing 75% of all observations. Here, the mean is 1,229.9 million Euros.

Table 22: Descriptive Statistics

Variable		Mean	SD	Median	Min.	Max.
Valuation, physical assets, R&D, advertising						
Tobin's *q*		1.201	0.719	0.988	0.256	4.833
Market capitalization (million Euros) [1]	*MC*	6,236.8	16,754.5	1,694.8	1.145	284,382.5
Debt (million Euros) [1]	*DT*	2,480.8	11,794.3	474.0	0.012	272,578.9
Assets (million Euros) [1]	*AT*	8,242.6	27,329.5	2,124.9	53.302	552,355.0
No R&D (dummy)		0.461		0.000	0.000	1.000
R&D stock (million Euros) [2]	*RD*	1,523.1	4,156.2	269.9	0.674	41,731.9
R&D stock / assets [2]		0.180	0.174	0.128	0.000	0.812
No advertising (dummy)		0.750		1.000	0.000	1.000
Advertising stock (million Euros) [2]	*ADV*	1,229.9	2,836.3	306.3	0.724	22,989.3
Advertising stock / assets [2]		0.152	0.153	0.094	0.000	0.726
Trademark portfolios and their composition						
TM applications (= portfolio size)	*TM*	24.939	62.553	7.000	1.000	827.000
TM applications / assets [1]		0.008	0.013	0.003	0.000	0.104
Brand-creating TMs (= TM families)	*TMC*	2.652	7.314	1.000	0.000	137.000
TM families with 2 to 15 applications	*TMF1*	2.612	7.201	1.000	0.000	135.000
TM families with ≥ 16 applications	*TMF2*	0.040	0.246	0.000	0.000	4.000
Brand-developing TMs	*TMD*	6.250	19.884	1.000	0.000	365.000
Hedging TMs	*TMDH*	0.670	2.620	0.000	0.000	60.000
Modernizing TMs	*TMDM*	0.871	3.079	0.000	0.000	60.000
Extending TMs	*TMDE*	4.708	15.352	1.000	0.000	290.000
Extending TMs (line)	*TMDEL*	2.486	9.465	0.000	0.000	201.000
Extending TMs (brand)	*TMDEB*	2.222	7.140	0.000	0.000	155.000
Independent TMs	*TMI*	16.038	39.286	4.000	0.000	502.000
Countries						
US		0.324		0.0	0.0	1.0
Japan		0.206		0.0	0.0	1.0
UK		0.084		0.0	0.0	1.0
Germany		0.038		0.0	0.0	1.0
France		0.031		0.0	0.0	1.0
Canada		0.025		0.0	0.0	1.0
Taiwan		0.025		0.0	0.0	1.0
Australia		0.022		0.0	0.0	1.0
Italy		0.021		0.0	0.0	1.0
Sweden		0.020		0.0	0.0	1.0
Other countries		0.204		0.0	0.0	1.0

Notes: N = 1,735 observations. SD = Standard deviation.
[1] Real 2004 prices.
[2] Companies never performing or disclosing R&D or advertising expenditures, respectively, were excluded. R&D expenditures are available for 935 observations and advertising spendings are available for 434 observations.

Regarding trademark portfolios, companies on average filed 24.9 trademark applications. This measure ranges from 1 to 827 applications.[119] The measures reflecting the structure of trademark portfolios exhibit large heterogeneity. Independent trademark

[119] Note that the largest identified trademark portfolio owned by *Konami* (1,401 applications) has been excluded in the final dataset as this observation was identified as being an outlier. The portfolio with 827 applications belongs to *Procter & Gamble* (see Table 19).

applications made up the largest fraction of company portfolios, with a mean of 16 applications per observation. On average, 2.65 applications per portfolios created trademark families while 6.25 applications per portfolio were filed to develop these families further. Companies largely relied on extending existing brands. On average, 4.71 applications were dedicated to extensions. A mean value of 0.87 trademarks is reported for modernizing brands, and an average of 0.67 trademarks was found to be hedging.

Most trademark families had a small size. Although large trademark families including more than 15 applications were very scarce in company portfolios, *PepsiCo* had even four families of that size. This company filed 201 applications in total, of which 93 applications belonged to one of the four large trademark families. This example is noteworthy as *Pepsico* had nearly four times more trademarks in just four families than the 'average' company had in total.

Regarding companies' domiciles, more than half of the companies in the sample are from the US (32.4%) and from Japan (20.6%). This is followed by firms being located in the UK (8.4%), in Germany (3.8%), and in France (3.1%). The weak presence of Europen companies is due to two reasons. The main reason is that the companies in the sample needed to be publicly listed. If the listing of companies at stock markets is more common in one country than in another, there will naturally be more companies from that country in the sample. This explains the large fraction of US- and Japan-based companies.[120] While this explains the weak presence of European companies to a large extent, another reason is related to the particular trademark rights studied (i.e., CTMs): It is possible that if non-European companies enter the European market, they are more likely to seek Europe-wide protection by filing CTMs instead of filing multiple trademarks at the national level. As compared to European companies, which might still file national trademarks despite the advent of the CTM as a pan-EU right (Greenhalgh and Rogers, 2006a), the possibility of filing national trademarks additionally increases the share of non-European companies in the sample.

The industries covered in the sample are reported in Table 23. This table also includes several characteristics of the companies in these industries. The largest share of companies operates in 'transportation, communications, and infrastructure' (11.7%). Other

[120] Data from the Reuters database substantiate this reason: Of the 6,500 largest worldwide companies that are stock market-listed, 25% have their domicile in the US and 19.1% in Japan.

large industries include ‘services’ (9.3%), ‘electronics and components’ (8.1%), ‘machinery and computer equipment’ (7.8%), and ‘chemicals’ (6.7%).

Table 23 reveals large differences between the company populations of the various industries. While some industries such as ‘services’ (mean of total assets: 3,917 million Euros) or ‘chemicals’ (mean of total assets: 4,435 million Euros) consist of smaller companies, others such as ‘transportation equipment’ (mean of total assets: 18,097 million Euros), which contains car manufacturers, include larger companies. These differences are also reflected in the Tobin’s *q* values. The average Tobin’s *q* in the ‘transportation equipment’ industry is 0.88, indicating that the market value of these companies is below the value of their physical assets. This is contrasted with companies operating in ‘biotechnology and pharmaceuticals’, whose mean Tobin’s *q* of 1.97 appears to be more than double of that in ‘transportation equipment’. When estimating the market value equation, a set of industry dummies will account for these differences.

The trademark activity of the companies also appears to be heterogeneous. Companies in ‘biotechnology and pharmaceuticals’ companies have filed 107.2 trademark applications on average and hence show intense trademark activity (see also Malmberg, 2005). This is in contrast to companies in ‘transportation, communications, and infrastructure’, which on average only brought 18.1 applications to the OHIM even though they have a mean of total assets similar to those in ‘biotechnology and pharmaceuticals’. In all industries, companies filed more brand-developing trademarks than brand-creating trademarks. The ratio of brand-developing to brand-creating trademarks, however, reveals variations and indicates different accentuations. In some industries, an emphasis is put on brand creation while in others brand development is more prominent. Industries that seem to accentuate brand creation, showing fairly low values of this ratio, are ‘food and kindred products’ and ‘chemicals’. Companies in ‘machinery and computer equipment’ and ‘instruments for measuring, analyzing, and controlling’ exhibit higher values and hence put more emphasis on brand development.

The way in which companies develop their existing brands can be analyzed when relating the number of hedging, modernizing, and extending trademarks to the total number of brand-developing trademarks. This allows an assessment of industry-specific emphases of different trademark filing strategies. Extension strategies are the

Table 23: Industry Characteristics

Industry	Obs.	%	Σ TMs	Ø total assets (million Euros)[1]	Ø Tobin's q	Ø TMs: Total	Creating brands	Devel-oping brands	Hedg-ing brands	Mod-ernizing brands	Extend-ing brands	Inde-pendent
Transportation, communications, and infrastructure	203	11.7%	3,670	13,500	1.105	18.1	2.5	6.3	0.8	0.6	4.9	9.3
Services	161	9.3%	2,651	3,917	1.506	16.5	1.9	4.4	0.4	0.6	3.5	10.1
Electronics and components	140	8.1%	4,071	5,346	1.172	29.1	3.1	6.7	0.7	1.1	4.9	19.2
Machinery and computer equipment	135	7.8%	3,007	4,836	1.142	22.3	2.3	4.4	0.6	0.7	3.1	15.6
Chemicals	116	6.7%	4,929	4,435	1.150	42.5	3.9	9.5	0.7	1.4	7.3	29.1
Retail trade	115	6.6%	1,910	5,007	1.424	16.6	1.9	4.0	0.6	0.5	2.9	10.7
Transportation equipment	99	5.7%	3,537	18,097	0.876	35.7	3.4	12.5	1.6	1.9	9.0	19.8
Food and kindred products	97	5.6%	2,782	5,202	1.201	28.7	3.6	9.9	1.2	1.8	6.9	15.2
Wholesale trade	94	5.4%	784	3,925	0.945	8.3	0.8	1.9	0.2	0.2	1.5	5.7
Instruments for measuring, analyzing, and controlling	58	3.3%	2,297	4,160	1.741	39.6	3.7	7.3	0.8	0.8	5.7	28.5
Primary metal industries	54	3.1%	560	3,924	0.922	10.4	1.0	2.0	0.2	0.3	1.5	7.3
Construction	52	3.0%	303	4,502	0.708	5.8	0.6	0.9	0.0	0.2	0.7	4.3
Biotechnology and pharmaceuticals	50	2.9%	5,359	12,594	1.969	107.2	11.5	20.5	0.9	3.0	16.7	75.2
Finance, insurance, and real estate	48	2.8%	730	34,915	1.217	15.2	1.7	4.3	0.5	0.5	3.3	9.2
Other industries	313	18.0%	6,680	8,883	1.165	21.3	2.1	5.0	0.6	0.6	3.8	14.2
Total	1,735	100%	43,270									
Mean				8,243	1,201	24.9	2.7	6.3	0.7	0.9	4.7	16.0

Notes: N = 1,735 observations.
[1] Real 2004 prices.

Table 24: Correlation Matrix

Variables	1.	2.	3.	4.	5.	6.	7.	8.	9.	10.	11.	12.
1. Tobin's *q*												
2. Assets	-0.069*											
3. R&D stock / assets [1]	0.243*	0.011										
4. Advertising stock / assets [1]	0.125*	-0.159*	-0.083									
5. TM applications / assets	0.174*	-0.364*	0.184*	0.266*								
6. Brand-creating TMs / assets	0.167*	-0.328*	0.149*	0.237*	0.794*							
7. Brand-developing TMs / assets	0.190*	-0.236*	0.142*	0.292*	0.763*	0.831*						
8. Hedging TMs / assets	0.075*	-0.141*	0.058	0.082	0.371*	0.473*	0.504*					
9. Modernizing TMs / assets	0.171*	-0.149*	0.124*	0.281*	0.474*	0.525*	0.637*	0.247*				
10. Extending TMs / assets	0.172*	-0.217*	0.129*	0.268*	0.730*	0.774*	0.948*	0.280*	0.455*			
11. Extending TMs (line) / assets	0.147*	-0.167*	0.135*	0.274*	0.598*	0.664*	0.768*	0.174*	0.366*	0.826*		
12. Extending TMs (brand) / assets	0.132*	-0.186*	0.081*	0.201*	0.590*	0.593*	0.775*	0.286*	0.374*	0.800*	0.323*	
13. Independent TMs / assets	0.129*	-0.350*	0.180*	0.200*	0.926*	0.562*	0.470*	0.208*	0.284*	0.459*	0.374*	0.373*

Notes: N = 1,735 observations. Pearson correlation coefficients with significance level: * $p \leq 0.01$.

[1] When computing correlation coefficients based on these variables, companies without R&D or advertising stocks, respectively, were excluded. R&D expenditures are available for 935 observations and advertising spendings are available for 434 observations.

most prominent strategy in all industries. However, comparing trademark filing strategies between industries reveals that the trademarks filed by companies in ‘transportation equipment’, ‘machinery and computer equipment’, ‘electronics and components’ and ‘food and kindred products’ more often have modernizing or hedging characteristics whereas trademarks filed by companies in ‘services’ and ‘biotechnology and pharmaceuticals’ more often have line- or brand-extending characteristics.

Table 24 reports the Pearson correlation coefficients of the variables that enter the market value equation. Asset ratios for all variables measuring intangible assets were used since these ratios are also used in the market value equation. Moreover by using these ratios, company size effects which might influence all variables are less likely to be captured by the correlation coefficients. Interestingly, all correlation coefficients with the dependent variable, Tobin’s q, are small. However, there are a number of high correlation coefficients. This is not unexpected because these coefficients involve trademark portfolio characteristics that are derived from the same source. It is important to note that practically all high correlation coefficients cannot distort the multivariate analysis since the variables that produce these coefficients are not used in the same estimation models.[121] Overall, the correlation coefficients between those variables that are commonly included in the same models appear to be fairly small.

4.6 Empirical Model and Results

In this section, the market value equation is estimated to examine the valuation of trademark portfolios that were produced by different filing strategies. I first present the regression equation, on which I ground the estimation of several models (Section 4.6.1). Then, the results of these models are reported (Section 4.6.2).

4.6.1 Multivariate Specification

The estimation of the market value equation employs the following regression equation:

[121] However, there are a few coefficients whose size needs to be noted. First, the number of trademarks that create brands and the number of trademarks that develop brands is highly correlated. Second, the correlations between independent trademarks and brand-creating, brand-developing, and extending trademarks are of moderate size.

$$\log\frac{V_i}{A_i} = (\sigma-1)\log A_i + \sigma\log\left(1+\gamma_{RD}\frac{RD_i}{A_i}+\gamma_{ADV}\frac{ADV_i}{A_i}+\sum_{j=1}^{s}\gamma_{TM,j}\frac{TM_{j,i}}{A_i}\right)+$$

$$\rho_{RD}z_{RD,i}+\rho_{ADV}z_{ADV,i}+\delta_{1,k}d_{1,k,i}+\delta_{2,l}d_{2,l,i}+\delta_0+\varepsilon_i\,. \qquad (30)$$

To account for the non-linear functional form of the regression equation, NLLS estimation is applied. To examine the valuation of trademark filing strategies, five different models will be estimated, all resting upon Equation 30. These models differ in the decomposition of companies' trademark portfolios. If this decomposition concerns s groups, the relative shadow value $\gamma_{TM,j}$ can be estimated for group j.[122]

As R&D and advertising stocks could not be computed for all companies, the non-availability is captured by the dummy variables z_{RD} and z_{ADV}.[123] Then, differences in valuations that originate from the unavailability of these variables will appear in the coefficients ρ_{RD} and ρ_{ADV}. To isolate overall variations in valuations, the regression equation includes a set of country and industry dummies (i.e., the regressors $d_{1,k}$ and $d_{2,l}$, respectively). For each set of dummies, the largest category has been chosen as the reference category. The reference country is the US (32.4% of all observations), and the reference category for industries is 'transportation, communications, and infrastructure' (11.7% of all observations).

4.6.2 Estimation and Discussion of Results

Table 25 reports the estimation results of the five models. For a comparison of these models, it is useful to highlight the differences in the decompositions of the trademark portfolios. In Model M1, no decomposition is used so that only the total number of companies' applications, *TM*, is included. In Model M2, the total number of applications is divided into brand-creating trademarks, *TMC*, brand-developing trademarks, *TMD*, and independent trademarks, *TMI*. Model M3 further decomposes *TMD* into the different kinds of brand development: hedging trademarks, *TMDH*, modernizing trademarks, *TMDM*, and extending trademarks, *TMDE*. In Model M4, extending trademarks are further split into those that are triggered by line extensions, *TMDEL*,

[122] Obviously, if no decomposition is applied, one trademark group leads to the estimation of one marginal value. As the decompositions involve more groups, several marginal values are estimated.

[123] Specifially, both dummy variables z_{RD} and z_{ADV} are set to one if R&D and advertising stock, respectively, are not available, and zero otherwise.

and those filings that have been initiated through brand extensions, *TMDEB*.[124] Model M5 includes trademark families instead of applications.

Before discussing each model in detail, the common observations between Models M1 through M5 are described. In doing so, I refer to Model M1. In all five models, the coefficient of the R&D intensity (i.e., the ratio of the R&D stock to assets) is highly significant (0.490, $p < 0.001$ in Model M1), and its size is rather stable. Other studies found similar values (Hall, 1993b; Hall *et al.*, 2007; Megna and Klock, 1993). Accordingly, capitalized R&D expenditures are positively associated with companies' market value. If interpreted as the relative shadow value of R&D, the size of this coefficient indicates that one Euro spent on R&D is equivalent to 0.49 Euros in physical assets. The coefficient of the advertising intensity (i.e., the ratio of the advertising stock to assets) is also significantly positive throughout all models (0.688, $p < 0.01$ in Model M1) and shows large consistency between the models. Again, there is a positive relationship between advertising stocks and company values, with one Euro spent on advertising corresponding to 0.69 Euros in physical assets. Similarities between the coefficients of both R&D and advertising have also been found by other researchers (Connolly and Hirschey, 1988). The coefficients of both dummy variables that address the non-availability of R&D and advertising investments are not significant throughout all models. This indicates that the absent or non-reported R&D and advertising data are unlikely to cause any variations in valuations. This is good news as it does not raise great concerns about sample selection (Hall and Oriani, 2006). In each model, both sets of dummy variables are jointly significant. Finally, the R^2 ranges between 0.278 and 0.284 and is thus similar to the values in other work employing Tobin's *q* formats. In all, these findings do not substiantially differ from previous work.

Model M1 contains the total number of companies' trademark applications, which has not been decomposed. The coefficient for total trademark applications is significantly positive (3.795, $p < 0.01$). Regardless of different trademark roles, companies' trademark activity is generally valued in financial markets, which is in line with other studies (Greenhalgh and Rogers, 2006a). The coefficient indicates that one trademark application is valued at approximately 3.8 million Euros in physical assets. As this

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[124] In Models M1 through M4, companies' trademark applications have been gradually decomposed, but the total number of trademarks considered is equal throughout the models; that is, the sum of all trademarks considered is the same in these models.

coefficient does not apply any decomposition, it has to be interpreted as an average value of any marginal trademark application regardless of its role in the portfolio.

Table 25: Market Value of Trademark Filing Strategies

Variables (dependent variable: Tobin's q)	**Model M1**	**Model M2**	**Model M3**	**Model M4**	**Model M5**
log(assets)	-0.015	-0.019 *	-0.019 *	-0.019 *	-0.017 $^{+}$
$(\sigma - 1)$	(0.010)	(0.010)	(0.010)	(0.010)	(0.010)
R&D stock / assets	0.490 ***	0.489 ***	0.483 ***	0.484 ***	0.485 ***
λ_{RD}	(0.138)	(0.136)	(0.135)	(0.136)	(0.136)
Advertising stock / assets	0.688 **	0.591 *	0.564 *	0.566 *	0.638 **
λ_{ADV}	(0.241)	(0.234)	(0.235)	(0.235)	(0.235)
Trademark applications / assets	3.795 **				
λ_{TM}	(1.399)				
Brand-creating trademarks / assets		-18.313	-20.119	-19.704	
λ_{TMC}		(18.707)	(19.058)	(18.936)	
Trademark families (2-15) / assets					19.770 $^{+}$
λ_{TMF1}					(11.093)
Trademark families (≥16) / assets					846.155 *
λ_{TMF1}					(394.199)
Brand-developing trademarks / assets		21.779 **			
λ_{TMD}		(7.815)			
Hedging trademarks / assets			16.750	16.256	
λ_{TMDH}			(15.373)	(15.548)	
Modernizing trademarks / assets			55.489 *	55.751 *	
λ_{TMDM}			(22.966)	(22.969)	
Extending trademarks / assets			17.984 *		
λ_{TMDE}			(8.754)		
Line-extending trademarks / assets				16.274	
λ_{TMDEL}				(10.664)	
Brand-extending trademarks / assets				19.387	
λ_{TMDEB}				(12.356)	
Independent trademarks / assets		0.443	0.343	0.328	0.851
λ_{TMI}		(1.715)	(1.708)	(1.716)	(1.763)
Control variables					
No R&D (dummy)	0.028	0.021	0.022	0.022	0.025
ρ_{RD}	(0.033)	(0.033)	(0.033)	(0.033)	(0.033)
No advertising (dummy)	0.003	0.001	-0.001	-0.001	0.005
ρ_{ADV}	(0.038)	(0.037)	(0.037)	(0.037)	(0.037)
Country dummies	Yes	Yes	Yes	Yes	Yes
Industry dummies	Yes	Yes	Yes	Yes	Yes
Constant	0.247 *	0.287 **	0.288 **	0.287 **	0.269 *
δ_0	(0.109)	(0.109)	(0.109)	(0.110)	(0.109)
Diagnostics					
R^2	0.278	0.283	0.284	0.284	0.283
Log likelihood	-1,045.67	-1,039.91	-1,038.33	-1,038.30	-1,039.92

Notes: N = 1,735. Estimation method: NLLS. Significance levels: $^{+}$ $0.05 < p \leq 0.10$; * $0.01 < p \leq 0.05$; ** $0.001 < p \leq 0.01$; *** $p \leq 0.001$. Reference group for industry: 'transportation, communications, and infrastructure'. Reference country: US.

In Model M2, total applications were split into brand-creating, brand-developing, and independent trademark applications. This allows comparing the valuation of brand-creating trademarks with brand-developing trademarks. While the coefficient of trademarks that develop families is significantly positive (21.779, $p < 0.01$), the coefficient of trademarks that initiate families is not significantly different from zero. The coefficient of independent trademarks, of which trademark families might arise as the trademark portfolio develops further, is also not significant. The interpretation of these coefficients is that only the development of brands is valued in financial markets. Trademarks that initiate these brands or trademarks that are not related to these brands do not contribute to companies' market valuations. This is interesting since investors in financial markets do not seem to simply value the number of trademarks that a company has. Instead, they value specific trademark roles and the benefits of specific strategies.

Model M3 splits the trademarks within a portfolio according to their filing strategies. Here, the valuation of trademarks that create, hedge, modernize, and extend brands can be assessed. The coefficient of hedging trademarks is not significant. However, both the coefficient of modernizing trademarks and that of extending trademarks are significantly positive (55.489 and 17.984, $p < 0.05$). As in Model M2, the coefficients of brand-creating trademarks and independent trademarks are not significant. The pattern of these coefficients indicates that financial markets do not value all enlargements of trademark families alike. The valuation of trademarks that extend brands can be explained by the informational leverage that these strategies involve. With extending strategies companies build upon an established brand and seek to induce spillover effects by transferring this brand to other products or other markets. These spillovers lead consumers to pool their experiences about products that share the same brand and potentially increase the market position of existing products as well as the success of new products (Dacin and Smith, 1994; Smith and Park, 1992). Investors seem to expect increasing future cash flows from extensions that seek to tap into the reputation of established brands, which is consistent with other research (Lane and Jacobson, 1995; Smith and Park, 1992). With modernizing strategies companies seek to cultivate and renew established brands. An explanation for investors who value modernizing strategies is that they maintain the strengths of existing brands and thus may also provide platforms for future extension strategies (Farquhar, 1989). Hedging strategies are not valued in financial markets. By definition, hedging trademarks occur when companies file very similar or nearly identical trademarks on the same day. I explain the finding that this strategy does not add value by the absence of potentials to generate cash flows. The fact that a new product is launched and the possibility that it generates future cash flows are fully reflected by a single one of the multiple applications filed. If a new product introduction is reflected by multiple trademark filings, this does not add value from an investor perspective. Put differently, investors do not expect additional cash flows from multiple trademark filings that differ slightly. That is because the number of trademarks simultaneously filed is obviously not related to the introduction of more products from which investors would derive future revenue streams.

In Model M4, extending strategies are further investigated. Splitting extending trademarks into two groups allows differentiating between line and brand extensions. The coefficients of those variables that already have been included in the regression equation of Model M3 remain unchanged. In Model M3, the coefficient of extending trademarks was significantly positive (17.984, $p < 0.05$). However, in Model M4, the coefficients related either to line or to brand extensions are not significant.[125]

Model M5 only includes trademark families.[126] To consider varying sizes of trademark families in the model, the number of families is split into smaller and larger families.[127] Through this split of the original measure of brand-creating trademarks, insights into the valuation of families with different sizes can be gained. Both coefficients of trademark families are positive and significant. However, the coefficient of larger trademark families (846.155, $p < 0.05$) clearly exceeds the coefficient of smaller families (19.770, $p < 0.1$). As indicated by the difference between the sizes of both coefficients, larger trademark families are more highly valued. Larger trademark families result from the extensive development of brands. Thus, this model again indicates that financial markets value those trademarks that develop brands. It seems that, if companies develop their brands, investors attribute future cash flows to these brands according to the extent of brand development. This finding is interesting as it is consistent with the observations of Models M2 and M3 that the development of trademark families is valued. Again, the effects of those variables that have already been included in other models are highly robust.

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125 It is possible that the deep level of portfolio decomposition does not allow for the estimation of a significant coefficient. Both variables carry zero values in a rather large fraction due to a large number of smaller trademark portfolios, in which extension strategies occur rather infrequently. Moreover, both variables are correlated ($r = 0.323$). It is also possible that the rule for separating line-extending trademarks from brand-extending trademarks is not appropriate for producing accurate estimates.

126 If only trademark families enter the model, brand-developing trademarks are implicitely considered because they are encompassed by the families.

127 Smaller trademark families include 2 to 15 trademark applications and larger trademark families 16 or more applications.

4.7 Conclusions

Brands are important intangible assets for companies. The ways in which companies create new brands and develop existing ones influence brand assets to a large extent. Corporate brand management deals with decisions of how the product portfolio is linked to the brand portfolio. As new products are introduced, companies can choose to either create new brands or to use existing ones. This results in a variety of brand types with some being applied only to one product while others cover a broad range of products. In the latter case, brand management has decided to use the same existing brand for several new product introductions. The impact of this brand management strategy on brand assets is rooted in the transferable reputation of a brand. When multiple products share the same brand, consumers correlate their beliefs about the qualities of these products (Erdem, 1998). When new products are launched under existing brands, consumers infer from their past experiences with the brand or its branded products the quality of the new products. In the marketing and business literature, research on brand strategies has a long history. The main characteristic of a brand, its differentiation potential, has often been used to define the brand as a construct. It is trademarks as IP rights, however, that ultimately underlie the mechanisms of a brand's differentiation potential (Phillips, 2003). As distinctiveness is a requirement for trademark registration, these very IP rights confer companies the legal instruments required to protect a brand against impairment and, hence, to maintain a brand's differentiation potential. Accordingly, the filing of trademarks reflects decisions of corporate brand management and provides insights into companies' brand assets. Surprisingly, trademarks that enshrine and protect company's brands have in empirical studies never been associated with companies' brand portfolios and their brand management. With the present study, I seek to fill this gap by analyzing how trademark filing strategies are associated with brand management and how these strategies contribute to the value of companies in financial markets.

Four different trademark filing strategies have been identified: creating, hedging, modernizing, and extending brands. The first strategy of creating brands involves trademark applications that are filed because the name or the sign of a new brand needs to be protected. This trademark filing strategy refers to the creation of new brands. Hedging is the second strategy and refers to a company's intense simultaneous filing of several very similar trademarks. A company employs this strategy to protect different facets of brands with multiple trademarks. Third, modernizing strategies correspond to the renewal of established brands to keep their appearance up-to-date and to maintain their strengths. The fourth strategy, extending brands, is used in order to extend established brands to cover new products, potentially with the purpose of leveraging existing brands in new markets.

I developed and employed a technique that reveals the structure of corporate trademark portfolios and establishes groups of trademarks that protect a brand. Moreover, this technique uncovered the role of trademarks and categorized them according to the filing strategies employed by companies. For several companies, the structures of their trademark portfolios have been presented and discussed to illustrate the linkages between trademarks and brands. The decomposition of trademark portfolios was then used with the market value approach to investigate the contribution of filing strategies to companies' valuations in financial markets. The market value equation was estimated with the financial, accounting, and trademark data of 1,734 companies.

The findings of this study may be valuable for both researchers and managers. They add to our understanding of how trademarks are linked to brands and how these linkages are valued by investors in financial markets. The findings of this study are based on a technique that reveals the structure of trademark portfolios, which provides formidable insights into a company's IP activities. It is shown that trademark portfolios include complex structures that protect companies' brands. This systematic technique allowed studying companies' brand management activities from a broader perspective since entire company portfolios and their development could be analyzed based on different strategies. The results indicate that financial markets value established brands. When using trademarks to investigate these brands and how they were developed, both modernizing and extending strategies were found to contribute to company values. The contribution of extending strategies to company value can be explained by the cash flow potential of relying on established brands to launch new products or to enter new markets. Extending strategies are a mechanism of informational leverage that tap into consumers' past experiences with a brand in order to induce quality inferences about newly introduced products. Financial markets expect future cash flows from extension strategies because advertising efficiencies occur with broader brands. Furthermore, the use of established brands to introduce new products – either in familiar or unknown markets – increases the likelihood of a successful introduction (Smith and Park, 1992). Modernizing strategies add value as they maintain the strengths of a company's existing brands. Notwithstanding that existing brands are protected by past trademark filings, companies file new trademarks to keep their brands' appearances up-to-date. Moreover, only a strong parent brand can provide a powerful platform for future extension strategies (Farquhar, 1989). Therefore, a company that neglects its existing brands risks its brands to be eroded, possibly affecting not only the parent brand itself but also related brands since consumers pool their experiences on the brand-level rather than on the product-level (Wernerfelt, 1988). Modernizing strategies allow companies to protect their already acquired assets against impairment and against obsolescence as time passes. Creating and hedging strategies did not add value. In summary, those strategies that regard subsequently filed trademarks and, thus, concern the gradual development of brands were valued by investors. The gradual development of brands leads to the emergence of trademark families, whose trademarks are interlinked and collectively protect a single brand. It is these groups of trademarks that are financially valued. Other trademarks which are filed without any linkages to existing trademarks were not found to be valued. From a financial perspective, companies that just engage heavily in filing trademarks to protect any kind of sign or term used in communication are less valued than companies that file trademarks to comprehensively protect their brands. Put differently, trademarks jointly protecting a brand are valued much more than 'loose' trademarks. 'Loose' trademarks are not associated with brands and are less likely to be legal anchors of brands because either their linkages to a brand are absent or cannot be observed (e.g., trademarks that protect slogans).

These results, however, do not come without caveats. Although objective data such as trademarks, financial statements, and stock prices were used, several limitations need to be mentioned. Although the technique of revealing the structure of trademark portfolios is replicable and unveils the role of trademarks within their portfolios, trademark filing strategies could be more accurately assessed if more detailed measures of how trademarks were applied to products were available: If the affiliation of trademarks with their products could be observed for all trademarks considered in the sample, more refined measures of trademarks and their associated strategies would result in a more accurate assessment of filing strategies and investors' valuations. Data of this kind are largely proprietary and thus were not available for this analysis although they would be available to company insiders. In this study, corporate trademark portfolios were built combining the CTM register with the world's largest companies. Relying on CTMs is reasonable because if large companies operate in Europe they are likely to seek EU-wide protection for their brands. Still, it cannot be ruled out that companies to some degree also rely on national trademarks to protect their brands. Supplementing the sample of companies with trademark data from other jurisdictions was not possible for this study as the CTM register was the only trademark register available that contained all trademark applications, including those that failed.

Areas for future research concern the relationship between brands as intangible assets and the trademarks that protect these brands. Instead of focusing on the valuation of assets, related research agendas might examine new product introduction processes or the choice of brand strategies. As the full range of manufactured goods and services can be protected by trademarks, these IP rights provide formidable instruments for performing systematic analyses that are not limited to certain industries. Furthermore, trademark data can be used to study companies' entire brand portfolios instead of focusing on individual brands as many other studies do. The technique of revealing the structure of corporate trademark portfolios presented in this study can also be helpful in assessing companies' simultaneous activities in different lines of business. Another challenging research question has been posed by Choi (1998), who stated that brand extension and R&D processes may be complementary. Ultimately, in order to deepen our understanding of the interactions and relationships between trademarks, brands, products, and other business activities, the role of trademarks as the 'legal root' of brands warrants further inquiry.

5 The Importance of Technology- and Market-Based Assets in Stock Movement

5.1 Introduction

Numerous studies have found that companies' technology- and market-based assets are valued in financial markets (e.g., Bosworth and Rogers, 2001; Cockburn and Griliches, 1988; Connolly and Hirschey, 1988; Greenhalgh and Rogers, 2006a, 2006b; Griliches, 1981; Hall, 1993b; Hall *et al.*, 2005; Hall *et al.*, 2007; Megna and Klock, 1993). These studies assume that publicly listed companies comprise bundles of assets whose values are day by day determined in financial markets (Griliches, 1981). Under the efficient market hypothesis, company values and thus stock prices include all future benefits that companies' assets are expected to generate (Fama, 1970). To identify technology-based assets, patents are regularly employed as they protect companies' technologies and allow researchers to observe companies' research efforts. To proxy market-based assets trademarks can be used, although they have been employed very rarely compared to patents (Mendonça *et al.*, 2004). Trademarks allow companies to bind consumers' experiences to signs or names thereby establishing direct connections with current and prospective customers. Researchers investigating the valuation of intangible assets have regularly employed annual observations of company values because technology- and market-based assets adjust rather slowly. For research questions concerning the valuation of intangible assets, annual observations are thus appropriate. However, this is in contrast to financial markets which move more rapidly as evidenced by high stock volatility (Ariff *et al.*, 1995; Fung, 2006). In financial markets, companies' market capitalizations can change drastically within the course of one year. Investment decisions are made more frequently, often on a weekly or even a daily basis. Of course, these movements are driven not only by companies' fundamentals but also by general macroeconomic influences as well as by investor sentiment[128] (Baker and Wurgler, 2006; Pindyck and Rotemberg, 1993). In addition to

[128] Investor sentiment can be explained by the systematic deviation between stock prices and companies' fundamentals in financial markets. Such mispricing may arise if investors behave collectively irrationally in forming their beliefs and preferences or in making investment decisions. This may lead to broad shifts in the

valuations of companies in financial markets, systematic patterns in the movements of stocks are also interesting for both researchers and investors.

Research concerning stock comovement analyzes the extent to which synchronous patterns of stock movement occur as well as why such patterns occur (Barberis *et al.*, 2005; Pindyck and Rotemberg, 1993). Numerous patterns of comovement in asset returns[129] have been found by researchers. For example, stocks with similar market-to-book ratios or similar technologies have been found to comove, as have stocks within the same industry, with the same nationality, or assigned to the same market index (Barberis *et al.*, 2005; Boyer, 2004; Chan *et al.*, 2003; Fama and French, 1993; Fung, 2003; Froot and Dabora, 1999; Greenwood and Sosner, 2007; Harris and Gurel, 1986; Jayaraman and Lee, 2005; Livingston, 1977; Peng and Xiong, 2006; Pindyck and Rotemberg, 1993; Vijh, 1994). Two broad theories have been identified to explain comovement (Barberis and Shleifer, 2003; Barberis *et al.*, 2005; Pindyck and Rotemberg, 1993): According to the traditional theory, comovement in stocks corresponds to comovement in companies' fundamentals. The value of a company, which is reflected in the stock price, equals the sum of all future cash flows discounted at a rate appropriate to its risk. Stock comovement must then be due to common sources: either symmetric changes in companies' cash flows or in their discount rates. Both future cash flows and discount rates are influenced by companies' assets, such that a correlation in fundamental values leads to stock comovement. This theory is regularly considered as the primary source of comovement. However, it assumes that the economy is frictionless and that investors are rational. These assumptions are challenged by a second class of alternative theories that represent the secondary source of comovement. In reality, economies are not frictionless and investors are often irrational. Hence, the strong connections between company values and fundamentals are weaker than theoretically projected, leading to mispricings and excess stock comovement that cannot be traced back to companies' fundamentals (Pindyck and Rotemberg, 1993; Shiller, 1989). The class of alternative theories thus draws upon 'friction-based' and 'sentiment-based' explanations. On a large scale, comovement can be symptomatic for stock market bubbles arising from broad waves of investor sentiment. Examples include the rise of biotechnology stocks in the 1980s or technology stocks in the late 1990s, both of which can be explained by investor sentiment (Baker and Wurgler, 2006; Cooper *et*

propensity to speculate and even to the occurrence of stock market bubbles (Baker and Wurgler, 2006). Investor sentiment is an important fundament of behavioral finance (Shleifer and Summers, 1990).

[129] For simplicity, an asset's change in price is referred to as its return.

al., 2001). Knowing the determinants of stock movement is important for portfolio management (Cornell, 2004; Elton *et al.*, 2003): Assume an investment manager selects two stocks for his portfolio. If both stocks moved in perfect synchrony, one investment would be redundant. If both stocks exhibit imperfect comovement or none at all, the investor is able to lower his risk exposure. Consequently, the investor buys stocks of various companies: companies in different industries, companies that invest in different technologies, companies selling their products to different markets, or simply companies in different countries. To control risk exposure and to select an adequate portfolio, an investor needs to understand the common factors behind patterns of stock movement. A company's fundamental value plays a major role, but in addition to the assets actually owned by a company, analysts' perceptions of that company are also important. When examining companies, investors draw upon categorizations or analogies (Zuckerman and Rao, 2004). For example, from 1998 to 2000 some analysts categorized *Amazon* as an Internet company and highlighted the analogies to *Dell Computers* (Beunza and Garud, 2007). Therefore, they usually derived buy recommendations. Other analysts classified *Amazon* as a book retailer like *Barnes and Noble* leading to more pessimistic sell or hold recommendations. This example indicates that in financial markets it is not only the fundamental values of companies that matter but also the ways in which analysts categorize them (Zuckerman and Rao, 2004).

The objective of this chapter is to deepen our understanding of the dynamics in financial markets and how they are linked to technology, product markets, and industries. More precisely, I seek to study the links between companies' fundamentals and the comovement of their stock returns. When analyzing patterns of stock movement, researchers have typically relied on accounting and financial market data such as dividend premiums, standard deviations of earnings per share, share turnovers, or total borrowings to assets (Ariff *et al.*, 1995; Baker and Wurgler, 2006). They also employed categories such as industries, countries, or indices. Other data that might better approach companies' fundamentals have not been used, except for Fung (2003) who found that technological linkages reflected in patent citations drive comovement. I seek to assess companies' technology- and product market-related activities by relying on their IP portfolios and observe these activities by their patents and trademarks. Note that this enables an examination employing more informative continuous measures instead of solely relying on discrete industry classifications. Such an approach also allows one to assess – and question – the appropriateness of seemingly objective industry categorizations instead of simply applying an existing classification scheme like a black box. I therefore also aim to investigate the relative importance of industry affiliations, technological activities, and product market positions in explaining the comovement of stock returns.

The following three main research questions are addressed: From the perspective of financial markets, are companies' fundamentals reflected in IP portfolios? Do companies' technology and product market activities lead to comovement in stock returns? How does comovement induced by technology and product market activities relate to industry-specific comovement? To address these questions, I use a dyadic approach, implying that the units of observation are not companies but rather pairs (or dyads) of companies. Comovement can then be observed for a specific company pair by drawing upon any metric that measures the association between both time series of stock returns. Companies exhibiting greater similarity in fundamental values should exhibit higher comovement. To assess the similarity within each company pair, the proximity of both companies' activities in the technology and product market space is measured. To obtain these proximity metrics, European IP rights that largely cover the same geographical region are used. Specifically, European Patents issued by the EPO and CTMs granted by the OHIM are considered. I employ multivariate regression techniques to examine the factors that drive comovement. To account for the pairwise data structure, which makes econometric estimations more complicated, the Quadratic Assignment Procedure (QAP) estimation method is applied. The data used comprise 177 worldwide, publicly listed companies in various industries from which 14,520 company pairs could be formed.

The results obtained in this study show that companies' proximity in technological activities and their proximity in product markets are important factors in explaining comovement of stock returns. This also indicates that data regarding IP portfolios such as patents and trademarks reflect companies' fundamentals from the perspective of financial markets. Of course, industry-specific comovement could also be observed but its explanatory power is partially absorbed by the technology- and product market-related variables that better reflect companies' fundamentals. This challenges the approach of solely relying on industry categorizations to capture companies' differences as they may not adequately account for companies' fundamentals (Mullainathan, 2002). Assessing the heterogeneity of companies within and between industries reveals that technologies, product markets, and industries are related to one another. Some industries appear to be more coherent than others in terms of the technologies companies draw or the markets in which companies sell their products. Some industries are closely linked to each other with regard to the technology or the product market space. This corroborates the findings of Zuckerman and Rao (2004), who note that industry classifications are, of course, helpful devices but that they may not be appropriate for all purposes to which they are applied.

The remainder of this chapter proceeds as follows. In Section 5.2, I present factors associated with comovement in stock returns and explain why comovement arises. This leads to a theoretical model, which is also presented in this section. Section 5.3 describes how the dataset used in this study was constructed. Descriptive statistics of these data are presented in Section 5.4. Moreover, this section indicates how comovement, industries, and activities in technology and product markets are related to each other. In Section 5.5, multivariate regression techniques are applied to estimate the factors that drive comovement. To account for the dyadic data structure, QAP is used for estimation, which is also outlined in this section. Section 5.6 concludes the chapter with limitations and an outlook for further research.

5.2 Sources of Comovement and Development of a Theoretical Model

To assess whether companies' technology and product market activities drive comovement, I use a dyadic approach, which has also been employed by Zuckerman and Rao (2004). The units of observation are therefore not companies but pairs of companies. Analyzing the pairwise correlation between stocks is, for example, an important task in portfolio analysis (Elton *et al.*, 2003). The degree of comovement within each pair is assessed by comparing the time series of the stock returns of both companies. The idea of the proposed model is to explain comovement within company pairs based on similarities in the fundamental values of this pair. To do this, I use the proximity within each company pair regarding companies' activities in both the technology and the product market space (Section 5.2.1). As there are reasons for the stock price to be delinked from companies' fundamentals, I also consider industry-specific comovement (Section 5.2.2) and other sources of comovement (Section 5.2.3). Finally, I present a theoretical model that accommodates these sources of comovement (Section 5.2.4).

5.2.1 Fundamentals-Based Comovement

The traditional theory of comovement holds that any comovement in stock returns is based on fundamentals (Barberis and Shleifer, 2003; Barberis *et al.*, 2005; Pindyck and Rotemberg, 1993). The assets owned by a company induce future cash flows that, if discounted at a rate appropriate to the risk and summed up, correspond to the market value of the company and, thus, the stock price. Comovement in the stock returns of two companies arises either if companies' earnings are correlated or if both discount rates are commonly affected (Barberis *et al.*, 2005). In this study, the fundamentals of companies are represented by their activities in the technology and the product market space.

To provide intuition, assume that two electronics companies are similar regarding the technologies they employ to produce their products, and that they are competitors in the same or in related markets. As these two companies are similar concerning both their technologies and their product markets, it is reasonable to argue that their fundamental assets will demonstrate greater similarity as compared to, for instance, a chemical company. Similar fundamental assets will induce correlated earnings or will lead analysts to apply similar discount rates. Financial markets aggregate the available information and form stock prices similarly for both companies. For example, investors may apply the same methods and the same assumptions to forecast future cash flows using, for example, the same estimated market growth for both companies or the same projected technological development confronting both companies (Zuckerman and Rao, 2004). Based on the similarities between these two companies, their stock returns should exhibit comovement. Such similarities also led to the comovement of technology stocks during the late 1990s (Baker and Wurgler, 2006; Zuckerman and Rao, 2004). Now, assume that two companies are in different industries, for example, one company is in electronics and one company is in chemicals. As these two companies employ different technologies to produce their products and, moreover, sell them to different markets, similarities regarding their technology and product market positions will be rather low. Put differently, their business models are built on different fundamental assets. Their stock returns should not exhibit high comovement when controlling for changes in macroeconomic variables that generally affect a broad range of stocks.

I argue that technology proximity between companies leads to a higher degree of comovement. Companies are regularly confronted with new opportunities due to technological progress. As new opportunities provide potential revenue streams in the future, the stocks of companies that are technologically close to one another will comove. Conversely, technologically similar companies will be subject to the same threats. Imagine a company that is confronted with radical technological change that may render the technologies underlying its current business obsolete (Benner, 2008). Researchers have argued that technological change of that kind triggers declines in stock prices for incumbent companies (Hobijn and Jovanovic, 2001; Laitner and Stolyarov, 2003; Pastor and Veronesi, 2005). Such declines in stock prices can be explained in two ways. First, comovement may arise due to similar sources of earnings rooted in similar assets. Second, such situations commonly increase the discount rates for a group of companies leading to symmetrical devaluations. Technological activities have been found to be associated with both the comovement of stocks and stock volatility. This has been shown by studies relying on knowledge spillovers and research overlap, two measures also obtained from patent data but constructed from patent citations (Fung and Chow, 2002; Fung, 2003, 2006). Investigating the valuation of companies, Hall *et al.* (2005) found that the valuation of patents is not symmetrical for all companies but differs across technological areas.

Product market proximity can also determine comovement. The explanation is similar to that described for technology proximity. The future prospects of companies that sell their products to similar product markets are commonly affected if conditions change in particular markets. The stock prices of these companies should then comove. Trademark data are used to identify companies' product market positions. This is possible because trademarks are regularly affiliated with products and therefore represent a company's visible front-end to customers. When assessing companies' future performance, investors consider the earning power of companies' market-based assets such as trademarks or brands (Srivastava *et al.*, 1998). Trademarks have been found to contribute to company values (Greenhalgh and Rogers, 2006a, 2006b). Brands, which are closely related to trademarks, have also been found to matter in financial markets (e.g., Barth *et al.*, 1998; Kallapur and Kwan, 2004; Lane and Jacobson, 1995). Trademarks are able to represent the product market position of a company. As a measure that compares the product market positions of two companies, product market proximity should therefore drive comovement.

5.2.2 Industry-Specific Comovement

The stocks of companies in the same industry have been found to exhibit substantial comovement (Livingston, 1977; Pindyck and Rotemberg, 1993). In financial markets, large numbers of companies are classified into categories (Barberis and Shleifer, 2003). Categorizations of companies in industries aim to form rather coherent groups of companies. As suggested by traditional theory, industry-specific comovement can then be attributed to correlations in companies' fundamentals. Industry-specific comovement can also be explained, however, by alternative theories of comovement derived from market frictions or investor sentiment (Barberis and Shleifer, 2003; Barberis *et al.*, 2005; Pindyck and Rotemberg, 1993). To explain comovement, Barberis *et al.* (2005) proposed the habitat view and the category view.[130] The habitat view suggests that investors tend to invest their funds in preferred industries. Because such habitats align the demand or the supply for certain categories, industry-specific comovement of stock returns may result. Another explanation is based on the category view. Investors are not able to simultaneously track all available securities they might be able to invest in either because there are limitations in processing information regarding thousands of securities or because costs incur when obtaining such information (Veldkamp, 2006). For simplification, investors choose categories such as industries to invest in (Mullainathan, 2002). If investors direct their funds on the industry-level instead of the company-level, industry-specific comovement occurs. Stocks can be categorized in many different ways besides industries leading researchers to study the phenomenon of category-level trading (Barberis and Shleifer, 2003; Barberis *et al.*, 2005; Boyer, 2004; Peng and Xiong, 2006; Wouters and Plantinga, 2006).[131]

Industry classifications may neglect important differences in companies' fundamentals within the same industry. The appropriateness of categorizing companies into industries has been assessed by the 'within-industry' similarity of the assigned companies. This measure of industry coherence has been shown to vary widely between industries (Zuckerman and Rao, 2004). Moreover, as time passes, new industries might emerge, and previous categorization schemes may not appropriately account for such emerging industries or may not change quickly enough (Barberis and Shleifer, 2003; Mullainathan, 2002; Zuckerman and Rao, 2004). Assessments purely based on industries may thus hamper correct comparisons of companies. I argue that industry affiliations, technologies, and product markets should be considered jointly when assessing and comparing companies.

5.2.3 Other Sources of Comovement

Companies with shares listed in the same country exhibit country-specific comovement (Chan *et al.*, 2003; Froot and Dabora, 1999). Companies are confronted with country-specific factors such as the economic cycle of the country, regulation issues,

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[130] They also proposed the information diffusion view which, however, is primarily relevant when studying how the inclusion of a new stock in an existing stock market index affects the comovement of the newly included stock with the index (Barberis *et al.*, 2005; Harris and Gurel, 1986).

[131] Category-level trading is also known as style investing, a term coined by Barberis and Shleifer (2003).

tax changes, or subsidy policies. These factors commonly affect companies' future earnings, upon which investors base their valuations. The result is country-specific comovement. Additionally, the alternative theories used to explain comovement also apply here (Barberis *et al.*, 2005). The habitat view suggests that investors' preferences lead to comovement of stock returns. For example, investors may be 'home-biased' and may therefore choose to invest only in companies in their home country. Alternatively, not all investors have ubiquitous access to all worldwide-traded securities. For example, groups of investors may be allowed to buy stocks only in the country where they reside. According to the category view, investors invest their money on the country-level instead of analyzing each company. Both behaviors lead to country-specific comovement.

General developments in financial markets also drive comovement. Changes in macroeconomic variables resulting from news about the worldwide economy and its outlook (e.g., interest rates, development of oil prices, recessions, or threats of terrorism) generally affect investor sentiment and, thus, stock prices on a broad range (Bittlingmayer, 1998; Officer, 1973; Pindyck and Rotemberg, 1993; Schwert, 1989, 1990).

5.2.4 Theoretical Model

The model concerns dyads of companies and relates companies' comovement to similarities in their fundamental values while also accounting for an industry-specific component. Control variables capture both country-specific comovement and comovement related to general developments in financial markets. Therefore, the model proposed is:

$$C_{ij} = f(S_{Tij}, S_{Mij}, m_{ij}, c_{ij}, \sigma_{ij}). \tag{31}$$

Comovement, C_{ij}, as the dependent variable, refers to the association between the stock returns of companies i and j. In this study, comovement will be operationalized by the correlation coefficient of stock returns (Zuckerman and Rao, 2004).[132] The similarity within pairs of companies is captured by the proximity of the technology positions of both companies, S_{Tij}, and the proximity of their product market positions,

[132] Other studies use betas or R^2 measures to investigate the comovement of particular stocks with a group of stocks (such as stocks included in a stock market index or stocks in specific industries) (e.g., Barberis *et al.*, 2005; Boyer, 2004; Fung, 2003; Roll, 1988).

S_{Mij}. Industry-specific comovement exists if both companies in the pair are in the same industry, captured by m_{ij}. Country-specific comovement is treated similarly and exists if both stocks are listed on stock exchanges in the same country, captured by c_{ij}. Comovement induced by overall developments in financial markets is captured by σ_{ij}. This variable measures the degree of comovement in both stocks that can be attributed to changes in the overall market (Elton *et al.*, 2003). To capture general market trends, a stock market index can be used that, for example, includes a worldwide collection of stocks. Before I explain the construction of this variable, I first present how the similarity within each company pair is modeled.

To identify the proximity within a company pair in the technology space, Jaffe (1986) used the uncentered correlation coefficient. He used the technological areas in which a company has patents to obtain a distribution vector for each company that represents the profile of its research interests. Using the vectors F_i for company i and F_j for company j, the proximity, S_{ij}, between the two companies i and j can then be calculated as follows:

$$S_{ij} = \frac{F_i F_j'}{[(F_i F_j)(F_{ji})]^{1/2}}. \tag{32}$$

This proximity measure produces the following values. If the distribution vectors for the activities of both companies are identical, the resulting value is one. If the activities of both companies are completely unrelated and the vectors therefore are orthogonal, the resulting value is zero. For all other pairs, the computed values range between zero and one, with values closer to one indicating a greater overlap between the activities of both companies.

Depending on the data used to generate the distribution vectors, the proximity between companies can be computed for different domains. To compute the technology proximity of two companies, S_{Tij}, the technological areas of a company's research interests are used to establish technology distribution vectors. Similarly, the proximity of two companies in the product market space, S_{Mij}, can be calculated when a product market-based classification is employed.

To account for overall changes in financial markets, the model includes a comovement component related to general developments in the financial market, σ_{ij}. This variable is derived from the single-index model (Elton *et al.*, 2003). In general, the single-index model states that comovement in security returns can be traced back to a single factor (Sharpe, 1963). One version of this model is the so-called market model, which uses a market index as the single factor and seeks to explain stock returns based on associations to overall market changes.

According to the single-index model denoted by

$$r_i = \beta_i r_m + \alpha_i + \varepsilon_i, \tag{33}$$

the return of stock i, r_i, depends on a systematic market-related component and an unsystematic firm-specific component. The systematic component is captured by the market return, r_m, weighted by the sensitivity of the stock returns to overall market returns, β_i.[133] The unsystematic component reflects the stock return which is independent of the market return, equaling the sum of the firm-specific constant, α_i, and a random element, ε_i.

The single-index model rests upon two assumptions (Elton *et al.*, 2003). The first assumption, which permits separating the stock returns into a systematic and an unsystematic component, is that the general market returns are unrelated to the idiosyncratic returns. Regression analysis can therefore be used to compute the betas with the overall market return as this method assures that ε_i and r_m are uncorrelated. Then, univariate regressions for each company provide the constants β_i and α_i. The second assumption is that idiosyncratic returns are unrelated between companies. Accordingly, the covariance between ε_i and ε_j is zero.

Based on these assumptions, the financial market-related comovement between two stocks, σ_{ij}, can be determined by

$$\sigma_{ij} = \text{cov}(r_i, r_j). \tag{34}$$

Applying Equation 33 results in

$$\sigma_{ij} = \text{cov}(\beta_i r_m + \alpha_i + \varepsilon_i, \beta_j r_m + \alpha_j + \varepsilon_j), \tag{35}$$

which can be transformed into

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133 β_i is a constant and r_m is a random variable.

$$\sigma_{ij} = \beta_i \beta_j \operatorname{cov}(r_m + \varepsilon_i, r_m + \varepsilon_j)\,. \tag{36}$$

The covariance between ε_i and ε_j is zero by assumption, and cov(r_m,r_m) equals the variance of r_m. Denoting the variance of r_m by the squared standard deviation of the market returns, σ_m^2, results in the following formula to compute the comovement component rooted in general developments in financial markets:

$$\sigma_{ij} = \beta_i \beta_j \operatorname{cov}(r_m, r_m) = \beta_i \beta_j \sigma_m^2\,. \tag{37}$$

In this section, I have presented a theoretical model to explain the comovement within dyads of companies according to their similarities in the technology and product market space. Before estimating this model, the dataset is presented.

5.3 Construction of Dataset

In this section, I describe how the dataset was constructed. I first mention the data sources and describe how the sampling proceeded (Section 5.3.1). After that, I explain in detail how the variables included in the theoretical model were operationalized (Section 5.3.2). The dependent variable and the regressors involve some important timing issues (Section 5.3.3).

5.3.1 Data Source and Sample

The data used in this study was collected from several sources. Companies' accounting and stock market data were drawn from the Reuters financial database. To carve out companies' technology and product market profiles required to compute the proximity within pairs, IP portfolios for both European Patents and CTMs were consolidated. European Patents were drawn from the PATSTAT database, and CTMs were obtained from the OHIM database.[134] Both IP rights cover largely the same geographical area. The CTM is a unitary pan-EU right, which is valid in all member states of the EU. This is not the case for the European Patent, which is a bundle of national patent rights and does not completely match the geographical area of the EU. To consolidate firm-level IP portfolios, patents and trademarks needed to be assigned to companies. To do this, the 'search engine logic' as described in the appendix was employed. This ap-

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[134] The PATSTAT database is the EPO Worldwide Patent Statistical Database licensed by the OECD-EPO Task Force on Patent Statistics. The October 2007 version was employed. The OHIM database is a copy of the register of CTMs administered by the OHIM in Alicante. It contains all trademarks filed until the end of 2004. Note that CTMs could be filed as of 1996 when the OHIM commenced its operations.

proach used a search pattern for each company name and assigned the appropriate patents and trademarks to each company. More precisely, a set of search patterns for each company was manually generated. These search patterns were then used to examine the full applicant lists within the patent and the trademark database in order to find those applicants that matched the original company list. This step was necessary because the companies in the original list were corporate entities listed on stock exchanges and the applicants applying for IP rights were legal entities. This very important distinction between corporate and legal entities stems not only from large corporations formed by multiple legal entities in various countries and business segments but also from spelling differences on behalf of the applicant or the granting authorities of the IP rights. Next, the patents and trademarks for each applicant considered were retrieved and subsequently pooled at the company-level.

A company was required to meet the following criteria to be included in the sample: (i) revenues exceeding 400 million Euros in its last income statement, (ii) being publicly listed on a stock exchange, and (iii) having at least ten European Patents and ten CTMs in its IP portfolio at the end of 2004.[135] Put differently, these selection criteria resulted in a sample consisting of large publicly listed companies that have substantial IP positions in Europe in terms of both patents and trademarks. Including non-European companies in the sample is crucial because US- or Japan-based companies also hold substantial IP positions in Europe. The sampling criteria led to 631 companies that, theoretically, form 198,765 (= 631 · 630 / 2) unique[136] company pairs. To reduce the computation effort caused by the pairwise data structure, I randomly selected 30% of these companies (i.e., 189 companies). Daily stock histories over several years were only available for 177 companies. Based on these companies, the final dataset could be built comprising 14,520 company pairs.[137]

5.3.2 Operationalization of Variables

In this section, the operationalization of the variables included in the regression is outlined. I begin with the variable measuring the comovement of stock returns. As

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[135] The third criterion is necessary for computing the proximity measures as they require sufficiently large IP portfolios regarding both patents and trademarks.

[136] Unique means that for two companies, A and B, only the pair AB is kept and the pair BA is dropped.

[137] Theoretically, 15,576 (= 177 · 176 / 2) unique pairs can be formed by 177 companies. However, the final dataset comprised fewer observations because, in some cases, either no IP activity was observed until 2002 or the stock histories were incomplete.

overall movements in the financial market induce comovement to some degree, I next present this variable. Thereafter, the computation of the proximity measures is explained and, finally, the industry classification used is outlined. The control variable that captures the country-specific component of comovement is not described in detail as its generation is straightforward (i.e., analogous to the dummy variable capturing industry-specific comovement).

5.3.2.1 Comovement of Stock Returns

In the theoretical model presented above, the dependent variable represents the comovement between the stock returns of two companies. Comovement is operationalized by the Pearson correlation coefficient (Zuckerman and Rao, 2004) and is defined as:

$$\rho_{ij} = \frac{n\sum_{t=1}^{n} r_{it} r_{jt} - \sum_{t=1}^{n} r_{it} \sum_{t=1}^{n} r_{jt}}{\sqrt{n\sum_{t=1}^{n} r_{it}^2 - \left(\sum_{t=1}^{n} r_{it}\right)^2} \sqrt{n\sum_{t=1}^{n} r_{jt}^2 - \left(\sum_{t=1}^{n} r_{jt}\right)^2}}, \tag{38}$$

where r_{it} is the stock return of stock i at time t, and n is the number of observations considered in the coefficient. r_{it} measures the percentage change between two subsequent observations of stock prices, p_{it} and $p_{i,t\text{-}1}$.[138] It can be computed by

$$r_{it} = \frac{p_{it}}{p_{i,t-1}} - 1. \tag{39}$$

Possible values of ρ_{ij} range from -1 to 1 and can be interpreted as follows: A correlation coefficient of 1 indicates that the returns of both stocks move synchronously and exhibit perfect comovement. A value of 0 indicates orthogonal stock returns, reflecting no comovement at all. Values between 0 and 1 indicate that the stock returns comove to some degree. If the value of the observed correlation coefficient is -1, the stock returns comove perfectly in opposite directions so that, for example, if one stock has a return of 5% in one week, the other stock has a return of -5% in the same week. Values between -1 and 0 thus also reflect comovement of stock returns which, however, systematically move in opposite directions.

[138] To be precise, the closing prices of each day, week, or month were employed.

To compute the correlation of the returns of two stocks, the observation frequency and the length of the time window had to be specified. Both characteristics are important because they determine the number of stock return observations considered to compute the correlation coefficient. The higher the observation frequency or the longer the time window, the more observations are used to compute the correlation coefficient. The number of observations is important as it influences the precision with which the correlation coefficient is computed. The observation frequency reflects the time that passes between two subsequent observations of stock prices. Regularly, daily, weekly, or monthly frequencies are used (Barberis *et al.*, 2005; Fung, 2003, 2006; Vijh, 1994; Zuckerman and Rao, 2004). The length of the time window indicates the period of time considered to compute the correlation. Normal lengths are one, two, or three years (e.g., Barberis *et al.*, 2005). For analyses that are more short-term oriented, a higher frequency is regularly used with a shorter time window. Correspondingly, a lower frequency is normally accompanied by a longer time window.

For operationalizing comovement, I concentrate on computing the correlation coefficient for a time window of three years and a monthly frequency for the observation of stock returns. To calculate each correlation coefficient, I therefore rely on 36 monthly observations of stock returns. However, to investigate the comovement for different frequencies, I also compute the correlation coefficients for all company pairs on a weekly basis for two years and on a daily basis for one year. Within a period of one to three years, companies' positions in product markets and technologies should remain rather stable. Jaffe (1986) argues that changes in technology and product market positions happen slowly. He states that technological expertise cannot be acquired quickly and that 'jumping' between product markets should not occur.

5.3.2.2 Financial Market-Related Comovement

To capture general developments in financial markets, the MSCI (Morgan Stanley Capital International) World Index was used.[139] The single-index model was applied to obtain the sensitivity of each stock to the overall market return represented by the MSCI (Elton *et al.*, 2003). Univariate regressions were run for each company to obtain

[139] The MSCI World Index is a stock market index that measures the stock market performance of developed financial markets and, as such, includes a collection of stocks from 23 countries (Website: http://www.mscibarra.com/products/indices/equity/definitions.jsp, accessed on November 17, 2008). It has been calculated since 1969 and is maintained by the company *MSCI Inc.* (formerly *Morgan Stanley Capital International*). For the remainder of this chapter, the abbreviation MSCI is used to refer to the MSCI World Index.

the betas with the overall market return required by Equation 37. These betas were then used to compute the MSCI-related comovement for each company pair. The calculations obviously needed to match the time window and frequency of the dependent variable. The three different frequencies of the dependent variable thus required the computation of MSCI-related comovement for daily, weekly, and monthly stock observations.

5.3.2.3 Technology Proximity

To measure the proximity of two companies in the technology and product market space, I employ the uncentered correlation coefficient as presented in Equation 32. Jaffe (1986) introduced this measure to assess the proximity between companies' technological positions in order to assess spillover effects. Other research also relied on this measure to study technological spillovers in light of product market rivalry (Bloom *et al.*, 2007). I rely on this measure to determine the proximity of companies in both the technology and the product market space. I first describe the measure that captures the proximity of companies' technological positions, and then the measure recording the proximity of their product market positions.

To compute technology proximity, the categories of a company's research interests as identified by patents were used to establish a technology distribution vector for each company (Jaffe, 1986). Companies' patents need to be classified into categories to obtain these vectors. Based on Equation 32, the technology proximity, S_{Ttij}, between two companies i and j at time t can thus be computed by:

$$S_{Ttij} = \frac{\sum_{v=1}^{30} P_{vti}^{stock} P_{vtj}^{stock}}{\sqrt{\sum_{v=1}^{30} \left(P_{vti}^{stock}\right)^2 \sum_{v=1}^{30} \left(P_{vtj}^{stock}\right)^2}} \tag{40}$$

P_{vti}^{stock} captures the company's patent stock in technology area v. I use 30 technology areas to categorize companies' patents and to form the distribution vectors for each company. European Patents are assigned to one or several IPC classes that characterize the technological fields of their subject matter. The PATSTAT database contains patent applications that distinguish between nearly 70,000 different IPC classes. Similarly to other research (e.g., Giuri *et al.*, 2007; von Graevenitz *et al.*, 2008), I use a classification system which aggregates these IPC classes into 30 technological areas.[140]

The patents held by a company need to be consolidated for each technological area. Note that each patent can be assigned to multiple IPC classes. Accordingly, a patent does not need to be assigned to one unique area of technology but rather might be assigned to two or three technological areas. A patent assigned to multiple technological areas is therefore fully considered regarding each of these areas. This approach is used because I seek to establish distribution vectors that reflect the profile of a company's research interests. Such profiles would not comprehensively reflect technological positions if I used only one of the assigned technological areas of such a patent.[141] This approach should not affect the results in a major way as the majority of all patents are assigned to only one technological area.

I do not simply count the patents for each company in each area but apply the so-called declining balance formula regularly used in research on patents (e.g., Hall and Oriani, 2006; Hall *et al.*, 2005; Hall *et al.*, 2007).[142] The declining balance formula assumes that today's patent stocks result from all past and present patents. The technological assets a company owns today result from past investments in R&D. Due to the obsolescence of technological knowledge, the technological assets instilled in the patent stock are assumed to depreciate at an annual rate δ. According to the declining balance formula, a company's patent stock in technology area v, P_{vti}^{stock}, is thus computed by:

$$P_{vti}^{stock} = P_{vti}^{flow} + (1-\delta)P_{v,t-1,i}^{stock} \,. \tag{41}$$

The influx into the patent stock in year t, P_{vti}^{flow}, is added to the patent stock of the previous year, $P_{v,t-1,i}^{stock}$, which has depreciated due to the time lapsed between t and $t-1$. Due to the depreciation rate, earlier patents will affect the stock less than more recent patents. For depreciation, a typical annual rate of 15% is used (Hall *et al.*, 2005; Hall *et al.*, 2007). The recursive nature of the declining balance formula requires an initial stock or full histories of past inflows to validly compute the current patent stock. I

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140 More specifically, the ISI-INPI-OST classification system was used. This classification system was established by the Fraunhofer Institute of Systems and Innovation Research (ISI, Germany), the Institut national de la propriété industrielle (INPI, i.e., French Patent Office), and the Observatoire des sciences and des techniques (OST, France). For the allocation of IPC classes to the technological areas of the ISI-INPI-OST classification system, see Hinze *et al.* (1997).

141 An analogous approach was chosen for trademarks to identify the product market activities of companies.

142 For details regarding the declining balance formula, see Hall (1990).

observe the full history of companies' patent activity in Europe. Thus, the initial patent stock is simply zero.

To determine the point of time at which a particular patent flows into the portfolio, I use the filing date of its patent application if it does not claim a priority application. In other cases, I use the earliest priority filing date. To explain the use of the priority filing date, it is useful to highlight the difference between a patent as a geographically limited right and a patentable invention. Assume that a company seeks to gain worldwide patent protection for an invention. Consequently, the company needs to gain a bundle of patents because each patent only covers the geographic area of the authority granting it. This bundle of patents is also known as a patent family. If, for example, a company decides to file a patent application with the United States Patent and Trademark Office first, and later files an application for a European Patent with the EPO, both patent applications will carry different filing dates although they relate to the same invention. However, in the second filing with the EPO, the company will claim the US application as a so-called priority application to inform the EPO that a patent application concerning this particular invention has already been filed. Using this approach to determine the year in which a particular patent flows into the patent portfolio ensures that the earliest observable date (at which the underlying invention enters the worldwide patent systems) is used, regardless of the country or region for which the company first seeks protection. Moreover, this date is independent from unintended delays in the patent granting process as well as from intended delays caused by strategic behavior of companies.

5.3.2.4 Product Market Proximity

Product market proximity is determined using an approach that is symmetrical to that measuring technology proximity. Von Graevenitz (2007) used this measure in studying trademark opposition behavior. Bloom *et al.* (2007) also computed product market proximity but they operationalized it by drawing upon the sales distribution over the industries covered by a company. However, industry classifications do not rely exclusively on product market-related factors to arrive at an appropriate categorization of companies. I therefore argue that, when assessing product market proximity, trademark data are superior as they are purely product market-related. Trademark data contain categories that inform researchers about companies' product market activities similarly to patents' technological areas. This allows the technology and the product market proximity to be determined with symmetric approaches.

Trademarks are always registered in relation to specific goods and services classes (European Council, 1993, Art. 38). These classes are organized in the Nice Classification, which consists of 45 classes that contain the full range of all possible goods and services (Mendonça *et al.*, 2004; WIPO, 2006). This classification system possesses 11 classes for services and 34 classes for manufactured goods.[143] There is a remarkable difference between IPC classes for patents and Nice classes for products. IPC classes are assigned to patent applications by the patent examiner during the examination process. There is no relationship between the legal protection of the subject matter and the IPC classes to which the patent is assigned. The Nice class of a trademark, however, is directly related to the breadth of protection. A trademark is protected only in its affiliated Nice classes. Thus, a few very well-known trademarks, like *Nestlé*,[144] are protected in all 45 Nice classes. Nice classes are not assigned by the trademark examiner. Instead, the applicant needs to apply for them when filing a trademark application and the examiner then investigates in which Nice classes trademark protection can be granted (European Council, 1993, Art. 38).

To compute product market proximity, the trademarks of a company are consolidated for each of the 45 Nice classes. This produces a vector that reflects the product market profile of each company. Comparable to patent data, a trademark can be affiliated with multiple Nice classes. Again, to generate the vector for each company, a trademark assigned to multiple Nice classes is included in each of these classes. This approach is reasonable because trademarks that cover several business lines are regularly protected in multiple Nice classes. Based on Equation 32, the product market proximity between two companies, S_{Mtij}, is thus computed as follows:

$$S_{Mtij} = \frac{\sum_{w=1}^{45} M_{wti}^{stock} M_{wtj}^{stock}}{\sqrt{\sum_{w=1}^{45} \left(M_{wti}^{stock}\right)^2 \sum_{w=1}^{45} \left(M_{wtj}^{stock}\right)^2}}. \tag{42}$$

The trademark stock, M_{wti}^{stock}, contains all trademarks filed by company i in Nice class w until time t. To arrive at these trademark stocks, the declining balance formula is not applied. A positive depreciation rate would indicate that trademarks are assumed to become obsolete over time. However, unlike patents which have an expiration period,

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143 Note that, due to revisions of the Nice Classification, only 42 classes could be considered until the end of 2001. Thereafter, 45 classes were considered (also discussed in Section 2.6.1).

144 CTM No. 2977569.

trademarks are indefinitely renewable. Furthermore, they often exist for decades, in some cases even longer than the companies that created them. The more a trademark is used in the course of trade, the more valuable it becomes. I therefore argue that trademarks do not depreciate. Trademark stocks can then be computed by

$$M_{wti}^{stock} = M_{wti}^{flow} + M_{w,t-1,i}^{stock}. \qquad (43)$$

As with patents, I observe the full history of companies' trademark activities in Europe. The OHIM database contains all trademark filings from 1996 when the OHIM commenced its operations until the end of 2004 when the OHIM database was recorded.

To determine in which year a trademark entered the trademark portfolio, I use the filing date of the CTM application instead of the registration date. Using the filing date ensures that one utilizes the earliest observable date at which a company seeks pan-EU protection for a particular sign. This date is independent of the sometimes lengthy process of trademark registration as well as any delays caused by legal actions of competitors.

5.3.2.5 Industry-Specific Comovement

The variable that captures the industry-specific component of comovement is generated by a comparison of both companies in each pair. If both companies are affiliated with the same industry, this dummy variable is set to one. Conversely, if both companies are in different industries, the variable takes the value zero.[145] To categorize industries, SIC codes are employed: Basically, the division structure of the SIC is used. In addition, more detail is added to manufacturing companies so that companies within this broad category can be differentiated. Ultimately, the companies in the sample are categorized into 23 industries, with the five largest categories comprising approximately 60% of the companies (see Table 26, discussed in Section 5.4.1).

5.3.3 Timing Issues Associated with Comovement and Proximity Measures

Both proximity and comovement measures contain data from time windows that last one to several years. The choice of which years to consider deserves special attention.

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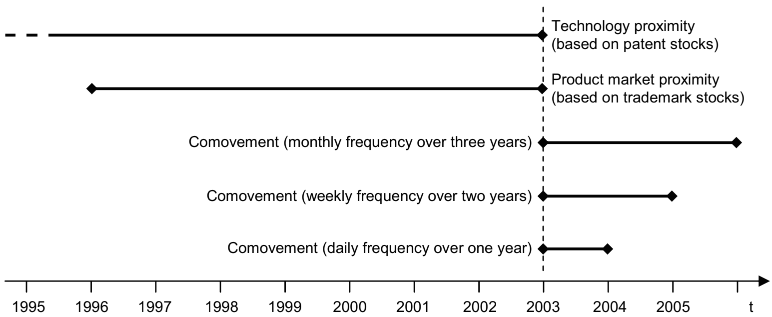
[145] Countries in which the stocks of the companies are traded are treated similarly. Country-specific comovement is therefore also operationalized by a dummy variable. If both stocks are listed on stock market exchanges in the same country, this dummy variable takes the value one, and zero otherwise.

Figure 12 indicates that both technology and product market proximity are based on patent and trademark portfolios that are accumulated over time. For both European Patents and CTMs, the full history of patent and trademark activity is observed. Patent and trademark portfolios and, thus, the proximity measures were recorded at the end of 2002. The central date for is study was January 1, 2003. Before this date, all patent and trademark data were used to compute the proximity measures between companies. As of this date, the stock prices were recorded to compute the correlation coefficients for stock returns in order to measure comovement. As mentioned above, this work focuses on the correlation coefficients computed from monthly stock returns over a three-year period. Additionally, higher frequency correlation coefficients with shorter time horizons are also employed as robustness checks. All comovement periods begin in January 2003 and run one, two, or three years.

Figure 12: Recording Proximity Measures and Comovement



According to the efficient market hypothesis (Fama, 1970), stock prices reflect all available information about a company and provide unbiased estimates of company values. Hence, it is important to explain what information from companies' patent and trademark portfolios is publicly available when the time window for observing co-movement begins.

In this study, all European Patents with application dates or priority filing dates prior to January 1, 2003 were considered. All of these patent applications will eventually become granted patents.[146] Due to ongoing examination procedures, a share of these patents will naturally be granted in 2003 or later. Not all of these documents can

[146] This is because I only considered granted patents in the dataset.

therefore be inspected by investors at the beginning of 2003 when the comovement periods begin. The key question is: When do investors in financial markets learn about the technological activities of companies? For the following reasons, I argue that, when the comovement periods begin, investors already have all the relevant information to appraise companies' assets and to estimate their valuations. First, the filing date of the patent application is crucial for companies as knowledge available before that date may prevent applications from being granted. After that date, companies may inform investors about their research interests. Second, companies publish their R&D efforts and research projects in financial statements, press releases and elsewhere, both to attract investors and to justify the R&D expenditures incurred. Third, R&D efforts leading to patent filings have normally been undertaken some time ago and have already affected companies' profits. Investors are able to learn about these R&D expenditures from companies' financial statements of 2002 and of previous years. In summary, I argue that financial markets are able to learn about companies' technological activities without knowledge of the patent applications that have been filed. Moreover, investors *cannot* draw on today's patent applications because they have not yet been disclosed. Ex-post, after they have been disclosed, patent applications and patent grants will prove companies' research efforts but without surprising investors. These considerations are in line with empirical findings. Several studies found knowledge assets to be valued in financial markets (e.g., Hall *et al.*, 2005; Hall *et al.*, 2007). Their results show that company values already embody companies' prospects given these technology-based assets even though the documents for these patents were not yet fully disclosed.[147] These considerations explain why the comovement periods begin immediately after recording patent portfolios at the end of 2002, and also why the comovement periods were chosen to not overlap with companies' patent filing activities.

Similar considerations apply to trademarks. All CTMs filed before the end of 2002 are considered. Again, by construction of the dataset, all of these filings become registered trademarks but obviously not all of them become registered before the beginning of the comovement periods. To determine companies' product market activities, the filing dates of the trademarks rather than the registration dates are informative. When filing a trademark application, companies denote the goods and service classes for which they seek protection, and therefore they have already chosen the markets in which they

[147] Patents were dated by their filing date. Thus, their application documents were not yet fully disclosed when companies' market values were recorded. Patents were still valued in financial markets.

want to sell their products. Obviously, companies will not wait until the event of trademark registration to inform their investors about their future plans. This is corroborated by Lane and Jacobsen (1995) who found that new product announcements (e.g., in trade journals) or companies' press releases affect stock prices. The date of trademark registration is therefore not informative for investors. Trademark filings do, however, reflect companies' activities in the product market space. Again, due to the trademark examination procedure, investors will not be able to learn about recent product market activities from the trademark register. For investors, trademark registrations can only provide ex-post evidence of companies' preceding decisions. Although they are not immediately observable for investors, trademark filings do reflect simultaneous product market-related activities. The comovement periods were therefore chosen to begin immediately after recording of the trademark portfolios at the end of 2002.

Having described how the dataset was constructed, descriptive statistics are presented in the next section.

5.4 Descriptive Statistics

I first present descriptive statistics for the companies in the dataset (Section 5.4.1). The pairs formed from these companies are then described (Section 5.4.2). As the proximity measures are a central element in this analysis, I show their relation to comovement (Section 5.4.3). Finally, I indicate how both technology and product market activities relate to industries (Section 5.4.4).

5.4.1 Companies

Descriptive statistics for the 177 companies in the sample are reported in Table 26. This table reports data from the end of 2002 when IP portfolios and accounting data were recorded. The accounting data listed in this table are not used for the estimation but are still shown to characterize the companies in the sample. On average, total assets of 17.9 billion Euros are reported. As can be seen from the standard deviation and from the divergence between the mean and median values, the distribution of company size is skewed. Among the companies, 54.2% disclosed their R&D expenditures. For these companies, the average R&D expenditures were 955 million Euros. Advertising expenditures were published by only 27.1% of the companies. The mean advertising expenditures for these companies were 550 million Euros. The mean and median values indicate that companies on average spent more money on R&D than on advertising. Concerning IP portfolios, which were used to identify companies' activities in the technology and product market space, the companies on average had 655.3 European Patents and 54.8 CTMs.

Table 26: Descriptive Statistics for Companies

Variable	Mean	SD	Min.	Median	Max.
Accounting data					
Total assets (million Euros)	17,898.9	34,732.7	313.9	5,770.9	283,186.6
R&D expenditures exist (dummy)	0.542		0.000	1.000	1.000
R&D expenditures (million Euros) [1]	954.7	1,608.6	4.8	259.9	8,554.3
Advertising expenditures exist (dummy)	0.271		0.000	0.000	1.000
Advertising expenditures (million Euros) [1]	549.8	789.0	3.0	179.9	3,863.3
IP portfolio					
European Patents [2]	655.3	1704.1	10.0	156.0	17487.0
CTMs [2]	54.8	95.5	10.0	26.0	668.0
Countries					
US	0.412		0.0	0.0	1.0
Japan	0.266		0.0	0.0	1.0
Germany	0.085		0.0	0.0	1.0
UK	0.040		0.0	0.0	1.0
Other countries	0.198		0.0	0.0	1.0
Industries					
Chemicals	0.164		0.0	0.0	1.0
Electronics and components	0.147		0.0	0.0	1.0
Machinery and computer equipment	0.136		0.0	0.0	1.0
Transportation equipment	0.130		0.0	0.0	1.0
Instruments for measuring, analyzing, and controlling	0.056		0.0	0.0	1.0
Food and kindred products	0.056		0.0	0.0	1.0
Paper and allied products	0.040		0.0	0.0	1.0
Transportation, communications, and infrastructure	0.040		0.0	0.0	1.0
Services	0.034		0.0	0.0	1.0
Primary metal industries	0.028		0.0	0.0	1.0
Other industries	0.169		0.0	0.0	1.0

Notes: N = 177 companies. Accounting data and IP portfolio data have been recorded at the end of 2002. SD = Standard deviation.
[1] Companies that do not disclose their R&D or advertising expenditures, respectively, were excluded. R&D expenditures are available for 96 observations and advertising expenditures for 48 observations.
[2] These variables reflect the sampling criterion because IP portfolios were required to have at least ten patents and ten trademarks at the end of 2004.

The distribution of the countries reveals that the companies in the sample were mainly from outside Europe. 41.2% of the observations were from the US, 26.6% from Japan, 8.5% from Germany, and 4% from the UK. The share of European companies appears to be rather low. The main reason is that companies were required to be listed on stock markets. If the share of publicly listed companies is generally higher in countries like the US or Japan due to differences in capital market structures, the sample will naturally contain a higher share of companies from these countries.[148]

[148] This is substantiated by data from the Reuters database: Of the 6,500 largest worldwide companies that are stock market-listed, 25% have their domicile in the US and 19.1% in Japan.

Regarding the distribution of industries in the sample, 16.4% of the companies operated in ‘chemicals’, 14.7% in ‘electronics and components’, and 13.6% in ‘machinery and computer equipment’. It can be seen that patent-intense industries are more highly represented in the sample due to the requirement that companies hold at least ten patents. This is in line with Fung (2003, 2006), who focused on similar industries when relating companies’ technological characteristics to comovement and stock volatility. Companies were also required to possess substantial trademark activity. However, it is reasonable to argue that this requirement did not exclude any industries. Basically all companies, regardless of their industries, file trademarks.

5.4.2 Company Pairs

Having described the companies in the sample, I now present the company pairs formed from the above described companies. Table 27 reports descriptive statistics for the 14,520 company pairs, which will be used for estimation in Section 5.5. For comovement as the dependent variable, three different correlation coefficients of companies’ stock returns were computed. These variables differ in the frequency of observations and the length of the time window used to calculate the correlation coefficients.

Table 27: Descriptive Statistics for Company Pairs

Variable		Mean	SD	Min.	5% perc.	Median	95% perc.	Max.
Comovement of stock returns	ρ							
Monthly returns over three years		0.137	0.201	-0.569	-0.057	0.138	0.317	0.819
Weekly returns over two years		0.168	0.130	-0.277	-0.035	0.162	0.391	0.751
Daily returns over one year		0.101	0.115	-0.264	-0.194	0.084	0.465	0.804
MSCI-related comovement	σ							
Monthly returns over three years [1]		0.637	0.963	-8.056	-0.000	0.434	0.034	16.959
Weekly returns over two years [1]		0.161	0.132	-0.036	0.017	0.128	0.414	1.196
Daily returns over one year [1]		0.012	0.011	-0.008	-0.131	0.009	2.229	0.081
IP portfolios								
Technology proximity	S_T	0.213	0.220	0.000	0.008	0.135	0.715	0.999
Market proximity	S_M	0.273	0.252	0.000	0.000	0.195	0.789	1.000
Categories of companies								
Same industry	m	0.098		0.000	0.000	0.000	1.000	1.000
Same country	c	0.247		0.000	0.000	0.000	1.000	1.000

Notes: N = 14,520 company pairs for 177 companies. Comovement data were computed for time windows starting at the beginning of 2003. Proximity data rest on IP portfolios that were recorded at the end of 2002. SD = Standard deviation. perc. = percentile.
[1] For convenience, these variables have been multiplied by 1,000.

The correlation coefficients that measure the comovement between stock returns show considerable heterogeneity. While the 95th percentiles indicate moderate comovement, a substantial number of observations below zero represent stock returns that comove in opposite directions. The correlation coefficients have a positive mean value, demonstrating a weak degree of comovement on average. This is true for all different frequencies of stock return observations. The mean values appear to be within the ranges reported by Zuckerman and Rao (2004).

MSCI-related comovement captures common patterns in stock returns that can be attributed to general developments in financial markets. The mean of this variable decreases with shorter frequencies for observing comovement. Lower frequency stock returns level out short-term changes and are thus more strongly linked to general market conditions and companies' fundamentals.

The fundamentals of companies are reflected by proximities in the technology and the product market space. Both proximity measures demonstrate that, to a large extent, the company pairs include rather dissimilar companies. However, according to the 95th percentiles, a substantial number of pairs exhibit rather high similarity. The mean value of technology proximity is 0.213, and the mean value of product market proximity is 0.273. The first is significantly lower than the latter ($p < 0.001$), which however might also be rooted in the different classification systems used. Dummy variables indicate whether both companies in each pair are assigned to the same category. In 9.8% of all pairs, both companies operate in the same industry. 24.7% of all pairwise observations contain two companies that are based in the same country.

5.4.3 Proximity Measures and Comovement

To provide further insights into the pairwise dataset, I now present some examples of company pairs that exhibit high values regarding comovement, technology proximity, and product market proximity (see Table 28). A comovement of 0.888 for the three-year period was computed for *Cisco Systems* and *Sun Microsystems* reflecting strong comovement of the stock returns of these companies. Both companies produce technological equipment, with *Cisco Systems* focusing on computer hardware and *Sun Microsystems* on communications equipment. In addition, their headquarters are both in the same region of California. Financial markets are informed about the similar fundamentals of both companies that lead to a strong correlation in their stock returns. Table 28 shows that the similarity between both companies is also reflected in the proximity measures. Both companies exhibit a high product market similarity and a moderate similarity with regard to technology. The strong degree of comovement the other company pairs in Table 28 exhibit is not surprising; the companies clearly possess similarities, as reflected in the proximity measures, leading financial markets to form stock prices that comove.

Table 28: Examples of Company Pairs

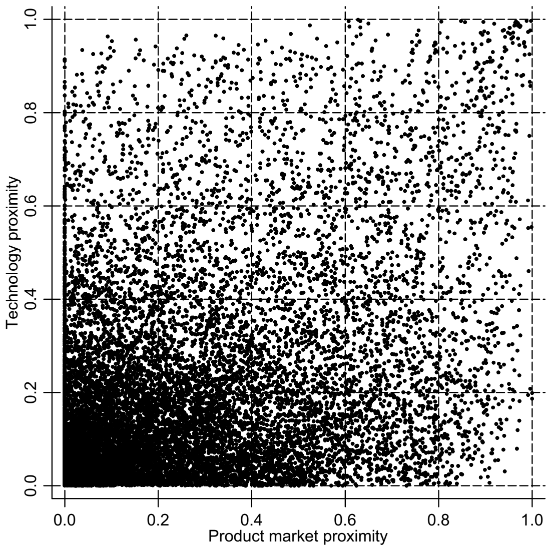
Company 1	Company 2	Comove-ment	Techn. proximity	Product market proximity
Examples of company pairs exhibiting high comovement ρ				
Cisco Systems, Inc.	Sun Microsystems, Inc.	0.888	0.456	0.934
International Paper Company	Weyerhaeuser Company	0.856	0.580	0.275
Delphi Corp.	Johnson Controls, Inc.	0.715	0.759	0.853
Dow Chemical Company	Eastman Chemical Company	0.712	0.967	0.894
Intel Corporation	Siemens AG	0.707	0.586	0.934
Examples of company pairs exhibiting high technology proximity S_T				
Honda Motor Co., Ltd.	Ford Motor Company	0.515	0.990	0.919
GlaxoSmithKline plc	Eli Lilly Co.	0.254	0.987	0.970
Intel Corp.	Microsoft Corp.	0.523	0.977	0.940
Ford Motor Company	Volvo AB	0.475	0.971	0.890
Novartis AG	Pfizer Inc.	0.115	0.951	0.983
Examples of company pairs exhibiting high product market proximity S_M				
Mazda Motor Corp.	Suzuki Motor Corp.	0.389	0.857	0.996
International Paper Company	Stora Enso Oyj	0.758	0.948	0.982
Takeda Pharmaceutical Company	Novartis AG	0.006	0.945	0.973
Oki Electric Industry Co., Ltd.	Alpine Electronics, Inc.	0.112	0.411	0.972
Motorola, Inc.	Siemens AG	0.469	0.759	0.966

Note: Comovement computed at a monthly basis over a three-year period.

Table 28 also includes examples with high technology proximities. The car manufacturers *Honda* and *Ford* belong to these examples, as do *GlaxoSmithKline* and *Eli Lilly*, both producing pharmaceuticals. The observed high technology proximity between *Intel* and *Microsoft* may be surprising. This example shows that categorizing companies' research interests into 30 areas may not yield a resolution high enough to differentiate sharply between such companies. The proximity measures are only able to distinguish between companies if their underlying technology distribution vectors are sufficiently different (Jaffe, 1986). However, due to the broad array of industries covered in this study, I deem 30 technological areas to be appropriate to distinguish between companies. This is reasonable to argue because a much higher resolution of research areas would imply that the uncentered correlation coefficient (i.e., the proximity measure) would indicate orthogonal activities even though companies might actually be weakly related. I close the discussion of Table 28 by highlighting some company pairs for which a high product market proximity was observed. These examples include *International Paper* and *Stora Enso*, both offering paper products. The pharmaceutical companies *Takeda* and *Novartis* were also found to possess a high product market proximity.

The examples in Table 28 provide first indications about comovement. In a next step, scatter plots are used to provide insights into how technology and product market proximity are related (see Figure 13) as well as how these measures are associated with comovement (see Figure 14 and Figure 15).

Figure 13: Technology and Product Market Proximity



The aim of Figure 13 is first to show the relationship between both proximity measures, and second to provide evidence that both measures indeed measure different domains in which companies' fundamentals can be analyzed. In this figure, each dot represents a company pair that is plotted with its product market proximity on the abscissa and its technology proximity on the ordinate. If both proximity measures were the same, all company pairs would fall on the diagonal, but this is obviously not the case. Both measures exhibit a Pearson correlation coefficient of 0.367. Although a concentration of pairs can be observed in the lower left area of the figure, the pairs are widely and independently distributed over both dimensions. Company pairs in the lower left area of the figure have low proximity values in both dimensions. The concentration in this area is not surprising since pairwise combinations of all companies associated with various industries have been formed. The upper right area indicates company pairs that are similar in both dimensions. The upper left and the lower right areas are interesting because the pairs located here reflect a high similarity in one dimension and a low similarity in the other dimension. For example, the lower right area contains company pairs that have a high product market proximity accompanied by a low technology proximity. According to Table 28, *Oki Electric* and *Alpine Electronics* is an example of a company pair with rather similar product market vectors but less similar technology vectors. To summarize this figure, neither product market proximity nor technology proximity is redundant. This is an important insight since this figure suggests that company comparisons should not solely rely on one dimension.

Figure 14: Comovement and Technology Proximity

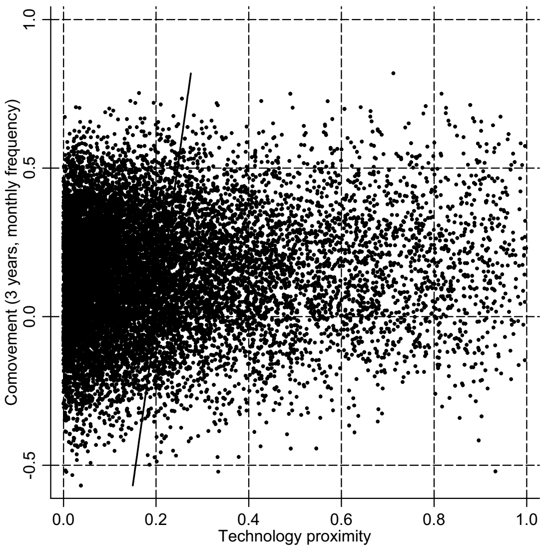
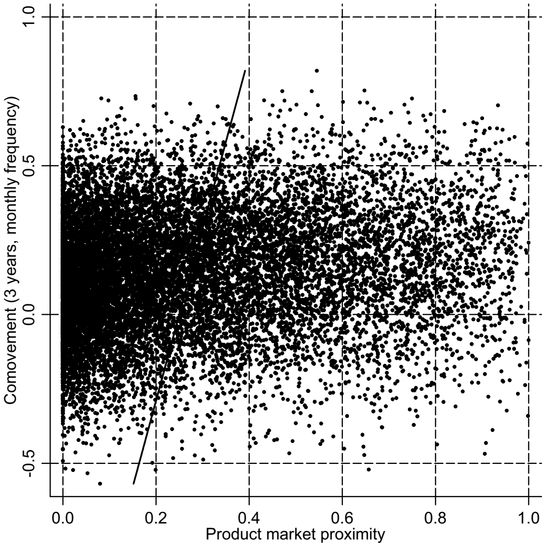


Figure 14 plots comovement over a three-year period against technology proximity.[149] The plotted line represents the fitted values of a univariate regression of comovement on technology proximity. This figure is interesting for the following reasons. First, as mentioned above, comovement within the company pairs does not center on zero. Instead, this figure clearly shows that the majority of company pairs exhibits positive, albeit weak, comovement. Second, a large fraction of the company pairs appears to be rather weakly related as indicated by low comovement values and low technology proximity values. Still, there is a considerable share of pairs that appear to have moderate or high technology proximity values. Third, the regression line has an upward

[149] The Pearson correlation coefficient between both variables is 0.082.

slope. This relationship will be assessed later when multivariate regression techniques are applied. Aside from the latter observation, these findings also largely apply to Figure 15, in which comovement is plotted against product market proximity.[150] Here, the cloud of dots has shifted to the right reflecting the significantly higher mean of the product market proximity mentioned above.

Figure 15: Comovement and Product Market Proximity



5.4.4 Proximity Measures and Industries

One of the objectives of this work is to show that companies' technology and product market activities add value in explaining stock comovement even though when accounting for the industry-specific component of comovement. Thus, I now examine the relationship between the proximity measures and the industries. To do this, all pairs are grouped according to their industry combinations resulting in an industry-by-industry matrix as shown in Table 29.[151] The industry combinations on the diagonal represent within-industry groups, which contain all pairs whose companies are in the same industry. The industry combinations below the diagonal contain all between-industry groups, and thus include all pairs in which the companies operate in different

[150] The Pearson correlation coefficient between both variables is 0.137.

[151] In addition, the table reports the number of companies in each group.

industries. For each industry combination, two values are provided. The upper value for each industry combination contains the mean value of technology proximity, and the lower value reports the mean value of product market proximity. Table 30 represents an addition to Table 29 that reports the number of observations used to calculate the means reported in Table 29.[152] Of course, industries populated by only a few companies need to be interpreted cautiously.

The insights provided by Table 29 are threefold. First, analyzing the within-industry groups on the diagonal permits an assessment of the homogeneity of the industries. Related work used the term ‘coherence’ to assess the homogeneity of industries (Zuckerman and Rao, 2004). High within-industry means of the proximity measures indicate a rather homogeneous group of companies either in terms of technology proximity, product market proximity, or both. Regarding both dimensions, ‘transportation equipment’ is populated by rather homogeneous companies. This is in contrast to other industries that are less homogeneous such as ‘instruments for measuring, analyzing, and controlling’ or ‘food and kindred products’. In ‘chemicals’, companies appear to be more homogeneous with regard to their technologies compared to their product markets. This pattern is reversed for companies in ‘electronics and components’ as well as for companies in ‘machinery and computer equipment’ as these companies are more homogeneous in terms of their product markets.

Second, examining the between-industry groups below the diagonal reveals interesting insights into the relationships of industries that are similar regarding the technology dimension, the product market dimension, or both. Companies in ‘chemicals’ or ‘food and kindred products’ draw on similar technologies. This may be explained by the process technologies employed by the companies in both industries. These two industries can therefore be considered as being at least to some degree technologically linked. Companies in ‘transportation equipment’ or ‘machinery and computer equipment’ are also technologically related. From a product market perspective, companies in ‘electronics and components’, for example, are related to companies in ‘machinery and computer equipment’ and ‘transportation equipment’.

[152] Due to missing values, the number of observations for each industry combination does not always reflect the maximum value of all possible company pairs. For example, 29 companies operate in ‘chemicals’ and 26 in ‘electronics and components’. This industry combination theoretically yields 754 pairs (= 29 · 26). However, due to missing values, this cell contains only 649 pairs for this industry combination.

Table 29: Technology and Product Market Proximity of Companies Within and Between Industries

Industry	Companies	1.	2.	3.	4.	5.	6.	7.	8.	9.	10.	11.
1. Chemicals	29	0.524										
		0.373										
2. Electronics and components	26	0.087	0.430									
		0.189	0.643									
3. Machinery and computer equipment	24	0.153	0.213	0.207								
		0.182	0.453	0.471								
4. Transportation equipment	23	0.093	0.197	0.274	0.565							
		0.113	0.306	0.362	0.604							
5. Instruments for measuring, analyzing, and controlling	10	0.179	0.191	0.149	0.112	0.366						
		0.231	0.405	0.325	0.191	0.433						
6. Food and kindred products	10	0.330	0.110	0.167	0.106	0.152	0.399					
		0.184	0.075	0.101	0.084	0.096	0.364					
7. Paper and allied products	7	0.224	0.101	0.236	0.097	0.147	0.293	0.736				
		0.151	0.215	0.246	0.138	0.172	0.137	0.687				
8. Transportation, communications, and infrastructure	7	0.135	0.256	0.196	0.230	0.125	0.168	0.150	0.250			
		0.159	0.449	0.328	0.265	0.259	0.132	0.316	0.544			
9. Services	6	0.139	0.298	0.219	0.249	0.151	0.135	0.139	0.244	0.182		
		0.215	0.669	0.484	0.358	0.401	0.103	0.219	0.481	0.670		
10. Primary metal industries	5	0.133	0.193	0.189	0.301	0.150	0.100	0.156	0.141	0.231	0.290	
		0.164	0.456	0.388	0.278	0.294	0.086	0.177	0.345	0.521	0.451	
11. Other industries	30	0.227	0.154	0.209	0.228	0.182	0.248	0.326	0.177	0.167	0.221	0.264
		0.176	0.254	0.238	0.231	0.188	0.142	0.254	0.291	0.297	0.253	0.228

Notes: N = 14,520 observations (pairs) for 177 companies. The values contained in columns 1 through 11 are computed based on unique company pairs (i.e., redundant pairs were eliminated): If A and B are companies, only the pair AB is considered while the pair BA is dropped. For each industry combination, the upper value is the mean value of technology proximity and the lower value the mean of product market proximity.

Table 30: Frequency of Company Pairs by Industries

Industry	Companies	1.	2.	3.	4.	5.	6.	7.	8.	9.	10.	11.
1. Chemicals	29	394										
2. Electronics and components	26	649	324									
3. Machinery and computer equipment	24	592	608	270								
4. Transportation equipment	23	579	589	547	253							
5. Instruments for measuring, analyzing, and controlling	10	276	247	222	218	45						
6. Food and kindred products	10	271	223	194	188	95	42					
7. Paper and allied products	7	189	173	161	155	65	65	21				
8. Transportation, communications, and infrastructure	7	179	176	159	157	65	64	47	18			
9. Services	6	156	156	144	138	56	55	42	41	15		
10. Primary metal industries	5	129	129	116	112	46	40	34	34	30	10	
11. Other industries	30	785	715	672	658	278	271	204	195	174	146	419
Company pairs with different industries = Lower triangle (without diagonal)		3,805	3,016	2,215	1,626	605	495	327	270	204	146	0
Company pairs with identical industries = Diagonal		394	324	270	253	45	42	21	18	15	10	419
Total companies	177											
Total observations		14,520										

Notes: N = 14,520 observations (pairs) for 177 companies. The values contained in columns 1 through 11 display the numbers of unique company pairs (i.e., redundant pairs were eliminated): If A and B are companies, only the pair AB is considered while the pair BA is dropped.

Third, the within-industry means of the proximity measures (i.e., the values on the diagonal) are generally larger than the between-industry means. This suggests that the industry classification used here does add value when categorizing companies. However, the insights gained from Table 29 also clearly demonstrate that solely relying on industry categorizations for analyzing or comparing companies can lead to biased results.

Thus, when analyzing the fundamentals of companies as investors in financial markets do, industry affiliations, technological activities, and product market positions need to be considered jointly. This substantiates the theoretical model presented above which will be estimated in the next section.

5.5 Estimation of the Theoretical Model and Results

In this section, multivariate regression techniques are employed to determine the factors that drive comovement. The pairwise nature of the data requires special attention because each company is included in multiple pairs. The observations are therefore non-independent which might lead to incorrect estimates of the standard errors. Thus, I first explain how to deal with this issue (Section 5.5.1), before I present and discuss the estimation results (Section 5.5.2). Then, various investigations to verify the robustness of the results are undertaken (Section 5.5.3).

5.5.1 Dealing with Non-Independent Observations in Dyadic Datasets

To understand the issue of non-independent observations when working with dyadic data, it is useful to imagine each variable of the pairwise dataset as a square matrix whose rows and columns both contain the same set of companies. In this matrix, each cell contains one value for one company pair. For example, a cell may capture the comovement or the proximity between the company given by the row and the company given by the column. There is one such matrix for each variable in the dataset. When imagining each variable of the dataset as a square matrix, it becomes obvious that all values in the same row (or column) come from the same company. This causes the problem that observations in individual rows or in individual columns tend to be highly correlated. In other words, the observations are not independent. For example, some Nice classes upon which the product market proximity is built are more densely populated than others. Of course, such densely populated Nice classes may reflect companies' demand for filing trademarks in these classes. However, the Nice Classification may contain classes that are more broadly defined, and others that are narrower.[153] Companies' product market positions, as identified by the classes of the Nice Classification, may therefore be biased due to the way the classes are defined in this scheme. The same also applies to technology areas that map companies' research interests. These reasons lead to non-independent observations. Yet, OLS estimation assumes that the observations are independent (Wooldridge, 2003). When employing OLS estimation, non-independent observations do not affect the consistency of the coefficient estimates, but the estimation of the standard errors is incorrect because the disturbance term is correlated across observations. The estimates of the standard errors are too small, leading to *p*-values that are too optimistic. To solve this problem, the standard errors need to be adjusted or the precision of the coefficient estimates needs to be assessed otherwise.

To validly examine the precision of the coefficient estimates, the QAP procedure is employed (Krackhardt, 1987, 1988; Simpson, 2001).[154] QAP is a resampling-based nonparametric technique that has similarities with bootstrapping methods. It has been commonly used in social network analysis. Networks consist of entities as nodes with connections between them as vertices. Network data can be organized in dyads, such that each observation represents a pair of connected entities with several variables characterizing the connection between the two nodes. To draw a comparison to this study, each company can also be viewed as a node, and pairs of companies are 'connected' by comovement measures, proximity measures, and other variables.

The idea of the QAP is illustrated in Figure 16. To use this procedure, an estimation method and a regression model must first be determined. In the present study, I use OLS estimation to estimate the theoretical model proposed to explain comovement. The QAP then proceeds in two steps. In the first step, the empirical sampling distributions for each regressor are established similarly to bootstrapping methods. A very important difference between the QAP and bootstrapping methods is that the latter generates a distribution that centers on the original size of the coefficient. QAP, however, produces a sampling distribution for each regressor that centers on zero. That is because each distribution obtained by the QAP corresponds to the null hypothesis,

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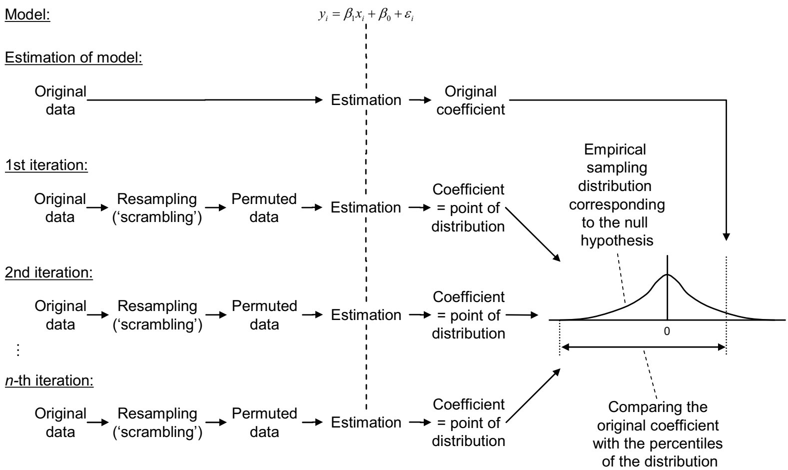
153 Class 9 of the Nice Classification is an example of a rather broad class as it contains trademarks related to all kinds of technical devices such as calculating machines, computers, recording discs, and also fire extinguishers. As indicated in Table 4, this is the most densely populated Nice class. This is in contrast to Class 23 which contains yarns and threads for textile use. This class is obviously narrower (WIPO, 2006).

154 In Stata, the program used for data analysis and statistics in this dissertation, QAP is implemented by the command 'qap'. With any regression model or even any estimation command, it allows accounting for pairwise data structures.

meaning that it forms a test statistic for the hypothesis that the dependent variable is unrelated to this regressor. In the second step, the size of each coefficient estimated by the original OLS regression is compared with its sample distribution obtained in the first step. Depending on the percentile of the observed coefficient in its empirical distribution, conclusions can be drawn whether the observed size of the original coefficient appears to be a random artifact of the data or whether it systematically deviates from the empirical sampling distribution.

Figure 16: QAP Estimation Method



The key element of the QAP is that for each regressor an empirical sampling distributions corresponding to the null hypothesis is formed. To arrive at an empirical sampling distribution that corresponds to the null hypothesis, enough points from the distribution need to be repeatedly obtained so that they collectively approximate the distribution. Here, I use 1,000 iterations.[155] During each iteration, the original dataset is randomly resampled such that for each regressor, a point from the distribution can be obtained when the regression equation is re-estimated. Each resampling needs to be conducted such that the dataset complies with the null hypothesis. For the manipulated dataset in each iteration, the relationship between the dependent variable and the regressors must therefore be removed, but the dependence within individual rows and individual columns must be preserved. This is performed by randomly 'scrambling'

[155] I use 1,000 iterations to approximate the empirical sampling distributions with 1,000 data points. Thus, when assessing its percentiles, *p*-value differences of 0.001 can be observed.

the dependent variable through a permutation of the regressors. Specifically, the rows and columns of the matrix are symmetrically permuted for the regressors but not for the dependent variable. In other words, the same permutation for both the rows and the columns is applied so that the rows and columns for single companies are not separated.[156] This assures that the dependence within the same row and the same column is preserved, but that the relationship between the regressors and the dependent variable is eliminated. Then, any relationship between the dependent variable and the regressors only occurs accidentally. Put differently, each permuted dataset itself complies with the null hypothesis. Because resampling by 'scrambling' is repeated multiple times, the empirical sampling distribution is formed which ultimately permits comparisons between the original coefficients and its distributions. The percentiles of the distribution are used to determine if the original coefficient lies at or near the boundaries of the distribution so that the null hypothesis can be rejected. Conversely, if the original coefficient lies somewhere in the middle of the distribution, the null hypothesis cannot be rejected and the original coefficient cannot be assumed to be significantly different from zero. In all, the QAP accounts for the pairwise structure of dyadic datasets.

To provide robustness for the results of the QAP procedure, each model is re-estimated by applying a second approach. This approach relies again on OLS estimation. However, as OLS estimation assumes independent observations (Wooldridge, 2003), the standard errors need to be adjusted to allow for intragroup correlation across all observations that belong to the same row.[157,158] Put differently, the standard errors are allowed to correlate within each row. I only allow intragroup correlation of standard errors within rows.

5.5.2 Estimation and Discussion of the Results

To investigate how the proximity measures and the industry affiliations drive the comovement of stock returns, several models are estimated. All of the models throughout this section rest upon the following regression equation which is based on the theoretical model developed in Section 5.2.4:

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156 An example of this 'scrambling' is provided by Simpson (2001).

157 It is important to note that only the standard errors and not the size of the coefficients are adjusted.

158 To implement this approach in Stata, I use the 'robust' and the 'cluster' options of the OLS estimation command.

$$\rho_{ij} = \delta_T S_{Tij} + \delta_M S_{Mij} + \delta_m m_{ij} + \delta_c c_{ij} + \delta_\sigma \sigma_{ij} + \delta_0 + \varepsilon_{ij}\,.^{159} \qquad (44)$$

All specifications estimated in this section contain a constant and the variables that control for MSCI-related comovement and country effects. The specifications vary with regard to combinations of industry effects and proximity measures. The estimation results from the QAP with comovement at a monthly frequency of stock return observations over a three-year period as the dependent variable are reported in Table 31.[160] Likelihood-ratio tests are computed to compare the models' goodness-of-fit. Model M1a solely incorporates the control variables and the constant. Models M2a to M4a include either industry effects *or* proximity measures. These models can be interpreted as 'horse race' regressions that allow separate comparisons of the contributions of industry effects and proximity measures. Models M5a to M7a include industry effects *and* different combinations of the two proximity measures to dissect the contributions of both variables in explaining comovement while also considering industry effects. Model M7a contains all variables. I first compare the estimation results with the expectations given by the theoretical model, and then compare the contribution of each of the variables in explaining comovement.

In all specifications reported in Table 31, the coefficients of the variables that were proposed to determine comovement behave as expected. The coefficient of technology proximity is significantly positive throughout all models. Companies that are technologically closer appear to have correlating stock returns. Market proximity is also found to be, in general, significantly positive. Similarly to technology proximity, companies that are closer to each other on the product market dimension also exhibit higher degrees of comovement. The variable capturing whether both companies are in the same industry is also significantly positive in all models. Thus, companies in the same industry exhibit a higher degree of comovement. Such industry-specific comovement has also been observed in other studies (Livingston, 1977; Pindyck and Rotemberg, 1993). The variable capturing whether the stocks of both companies in the

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[159] Note that σ is a so-called generated regressor. Still, this should not bias the results reported in this section since the QAP is similar to bootstrapping methods. Moreover, the data used to compute this regressor are independent of those of the other regressors.

[160] Note that the numbers in squared brackets are not standard errors but instead are p-values. The QAP analyzes the coefficients' precision by comparing the empirical sampling distribution that corresponds to the null hypothesis with the size of the coefficient. From these comparisons, percentiles can be obtained that can be converted to p-values, as indicated in Table 31.

Table 31: Estimation Results from QAP (Dependent Variable: Comovement at a Monthly Frequency)

Variables	Model M1a	Model M2a	Model M3a	Model M4a	Model M5a	Model M6a	Model M7a
IP portfolios							
Technology proximity			0.074 ***		0.060 ***		0.041 **
β_T			[<0.001]		[<0.001]		[0.008]
Product market proximity				0.078 ***		0.068 **	0.057 **
β_M				[<0.001]		[0.002]	[0.008]
Industry-specific component							
Same industry (dummy)		0.047 ***			0.032 ***	0.029 **	0.022 *
β_m		[<0.001]			[0.001]	[0.004]	[0.028]
Control variables							
Same country (dummy)	0.054 ***	0.053 ***	0.054 ***	0.053 ***	0.053 ***	0.052 ***	0.053 ***
β_c	[<0.001]	[<0.001]	[<0.001]	[<0.001]	[<0.001]	[<0.001]	[<0.001]
MSCI-related comovement [1]	0.071 ***	0.072 ***	0.072 ***	0.069 ***	0.072 ***	0.070 ***	0.070 ***
β_σ	[<0.001]	[<0.001]	[<0.001]	[<0.001]	[<0.001]	[<0.001]	[<0.001]
Constant	0.078 ***	0.073 ***	0.062 ***	0.058 ***	0.062 ***	0.058 ***	0.053 ***
β_0	[<0.001]	[<0.001]	[<0.001]	[<0.001]	[<0.001]	[<0.001]	[<0.001]
Diagnostics							
R^2	0.141	0.146	0.148	0.151	0.150	0.153	0.154
Log likelihood	3,831.85	3,872.19	3,888.51	3,913.54	3,905.49	3,928.07	3,941.86
Likelihood-ratio tests							
Compared model		M1a	M1a	M1a	M2a	M2a	M5a
2 · Δ(Log likelihood)		80.68 ***	113.32 ***	163.39 ***	66.60 ***	111.76 ***	72.76 ***
Compared model					M3a	M4a	M6a
2 · Δ(Log likelihood)					33.95 ***	29.05 ***	27.59 ***

Notes: N = 14,520 company pairs for 177 firms. Estimation method: QAP with 1,000 OLS estimation-based iterations. p-values in squared brackets.
Significance levels: * $0.01 < p \leq 0.05$; ** $0.001 < p \leq 0.01$; *** $p \leq 0.001$.
[1] This regressor has been multiplied by 1,000 causing its coefficient to deflate.

pair are listed in the same country is also positive and strongly significant. Consistently, country-specific comovement has also been found by other researchers (e.g., Chan *et al.*, 2003; Froot and Dabora, 1999). MSCI-related comovement reflecting overall developments in the financial markets is also strongly significantly positive throughout all models.

Each of the 'horse race' regressions (Models M2a to M4a) contains only one variable for companies' proximities or industry effects. Although industries, technologies, and product markets are not independent of each other, as has been seen in Table 29, these specifications are still estimated as they permit separately comparing the contributions of the proximity measures and the industry-specific component of comovement. Comparing the goodness-of-fit of these models reveals which of these variables explains comovement best. As can be seen from the likelihood-ratio tests, as denoted in Models M2a to M4a, all of the variables significantly increase the goodness-of-fit compared to Model M1a. However, not all variables increase R^2 to an equal degree. The largest increase can be seen for product market proximity (Model M4a). Technology proximity (Model M3a) also has a larger explanatory power than the industry effects (Model M2a).

In Models M5a to M7a, different combinations of proximity measures are included in addition to the variable capturing the industry-specific component of comovement. Model M5a shows two things. First, when accounting for industry effects, technology proximity remains significantly positive (0.060, $p < 0.001$). Second, R^2 significantly increased compared with models that only contained the industry-specific component or technology proximity (Models M2a and M3a, respectively). Model M6a includes product market proximity instead of technology proximity. Again, its coefficient is significantly positive (0.068, $p < 0.01$), and R^2 increased significantly. In Model M7a, both technology and product market proximity are included. Both proximity measures are significantly positive (0.041 and 0.057, $p < 0.01$). The industry-specific component is also significant and positive (0.022, $p < 0.05$). Each variable reflecting companies' proximity preserved its explanative power although industries, technologies, and product markets are not independent. Compared to the previous two models, R^2 increased strongly.

Next, the significance patterns observed upon successive addition of the regressors are scrutinized to investigate the value added by each regressor in relation to the other regressors. This tackles the question which contribution each variable delivers although industries, technologies, and product markets are related. The following interesting finding needs to be highlighted. One the one hand, as presented above, each variable reflecting companies' proximity is significant throughout all models. None of the variables is insignificant which would have led to the conclusion that one regressor is redundant when other variables are included. Accordingly, each variable adds value in explaining comovement. One the other hand, the explanatory power of each measure declines as more variables are included. This indicates the interrelation of industries, technologies, and product markets. This finding is discussed in detail as follows.

The sizes of the three coefficients representing the impact either of companies' proximity or of industry effects on comovement systematically decreased when other variables were successively added. Accordingly, the explanative power of each of these three variables was partially captured by the other variables.

The sharp decline of the coefficient of the industry-specific component of comovement requires special attention. This drop is particularly remarkable when compared to the country-specific component of comovement, which has been constructed similarly to the industry-specific component of comovement, but which hardly changed throughout the models. In Model M7a, the size of the country-specific component was 0.053 ($p < 0.001$), which can be interpreted as follows: The correlation coefficient of the stock returns of two companies listed in the same country is 0.053 higher compared to that of companies from different countries. This effect is large in light of the mean comovement, which is 0.137. The size of this coefficient is consistent across all models, implying that country-specific comovement appears to be independent of the other factors. The industry-specific component of comovement behaves differently. In Model M2a, the coefficient was 0.047 ($p < 0.001$) but it reduces to 0.022 ($p < 0.05$) in Model M7a. This sharp reduction is caused by the proximity measures which partially absorb the explanatory power of the industry-specific component.

Comparing Model M7a to models with fewer regressors, the sizes of the coefficients of the proximity measures are also smaller. However, their reductions are less drastic. Interestingly, the coefficient of product market proximity is higher than the coefficient of technology proximity (0.057, $p < 0.01$ vs. 0.041, $p < 0.01$). The future success of technological activities is rather uncertain leading to asymmetric information that in turn increases stock volatility (Fung, 2006). The degree of uncertainty in assessing future output may be lower if investors analyze companies' product market activities, simply because the sources of future revenue streams may be less blurred. The differing sizes of the coefficients may therefore be explained by investors having fewer difficulties in projecting future cash flows from product market activities than from companies' research efforts. However, another reason that cannot be ruled out is rooted in the different categorization schemes that were used to assess companies' activities in both dimensions.

Industry-specific comovement cannot be completely attributed to the industry itself as it at least partly captures other sources of comovement that are more clearly related to companies' fundamentals. An industry classification aims at categorizing companies in homogeneous groups. However, it may separate companies into different categories even though similarities regarding their technology or product markets may prevail. Companies separated by industries may still be rather similar in the technologies they use to build their products or in the markets in which they sell their products. I argue that analyses focusing on industry-specific comovement and solely relying upon industry classifications may therefore underestimate similarities in fundamentals. Or, in other words, my findings indicate that the degree of industry-specific comovement might be overestimated. Furthermore, a recent trend in the literature explaining comovement focuses on investors' trading behavior (Barberis and Shleifer, 2003; Barberis *et al.*, 2005). However, the observed reduction of the coefficient of the industry-specific component indicates that fundamentals at least partially absorb the effect of industry-specific comovement. This gives rise to the argument that industries or other categorization schemes may be useful devices for simplification but that other variables proxying companies' assets should also play a major role in company analysis. The appropriateness of such classifications should therefore not be taken for granted.

To summarize, these findings demonstrate that each measure reflecting companies' intangibles – i.e., technology-based and market-based assets – as well as industry categorizations add value in explaining comovement. The results also clearly show that industries, technologies, and product markets overlap to some degree but, at the same time, are not redundant.

5.5.3 Robustness Checks: Pairwise Data, Frequency of Comovement, and Proximity Measures

To analyze the robustness of the aforementioned results, the following three analyses are made. First, all models are re-estimated by applying an estimation method other than the QAP. Standard OLS regressions with adjusted standard errors to account for the pairwise structure of the data are conducted. Second, the dependent variable is replaced with comovement computed for higher frequencies of stock return observations. Third, I recalculate the proximity measures employing quality-adjusted patent and trademark stocks instead of simply counting patents and trademarks.[161]

As a first step, all models presented in Table 31 are estimated by employing standard OLS estimation with adjusted standard errors. Since QAP also relies on OLS estimation to obtain consistent coefficients, the sizes of the coefficients do not change. While the QAP compares the sizes of the OLS coefficients with the empirical sample distribution to assess their precision, the standard errors of the OLS coefficients are now adjusted for intragroup correlation. The results are shown in Table 32.[162] Both approaches produce consistent results. There are only minor changes regarding the precision of the coefficients (i.e., its significance levels).

In a second step, I assess the robustness of the results by replacing the dependent variable with comovement at higher frequencies of stock return observations. The results discussed above were obtained by employing comovement for monthly observations of stock returns as the dependent variable. Now, the full model is estimated for comovement with daily and weekly stock return observations over a one-year period and a two-year period, respectively (see Table 33). For each of these new dependent variables, the results were computed with both estimation methods. In general, the results show a rather high degree of consistency with those reported before. Compared to the models employing comovement for monthly stock return observations, R^2 increased strongly. As can be seen by the control variables, comovement based on daily or weekly stock returns is largely explained by the country-specific component and trading patterns that are related to financial markets in general (i.e., MSCI-related comovement). These effects seem to overlay fundamentals-driven movement as evidenced by the lower coefficients of the proximity measures and the industry-specific component (Models M9a and M9b). This reflects a “long run pressure towards fundamentals” (Barberis and Shleifer, 2003, p. 190). Nevertheless, the coefficients of

[161] Quality-adjusted patent and trademark stocks account for the dispersed value of these IP rights. The value of patents and trademarks has been found to be unevenly distributed.

[162] Note that regression diagnostics are omitted in Table 32 because they are identical with those displayed in Table 31.

Table 32: Estimation Results from OLS with Adjusted Standard Errors (Dependent Variable: Comovement at a Monthly Frequency)

Variables	Model M1b	Model M2b	Model M3b	Model M4b	Model M5b	Model M6b	Model M7b
IP portfolios							
Technology proximity			0.074 ***		0.060 ***		0.041 **
β_T			(0.011)		(0.012)		(0.013)
Product market proximity				0.078 ***		0.068 ***	0.057 ***
β_M				(0.013)		(0.013)	(0.014)
Industry-specific component							
Same industry (dummy)		0.047 ***			0.032 ***	0.029 ***	0.022 *
β_m		(0.008)			(0.009)	(0.009)	(0.009)
Control variables							
Same country (dummy)	0.054 ***	0.053 ***	0.054 ***	0.053 ***	0.053 ***	0.052 ***	0.053 ***
β_c	(0.008)	(0.008)	(0.008)	(0.008)	(0.008)	(0.008)	(0.008)
MSCI-related comovement [1]	0.071 ***	0.072 ***	0.072 ***	0.069 ***	0.072 ***	0.070 ***	0.070 ***
β_σ	(0.006)	(0.006)	(0.006)	(0.006)	(0.006)	(0.006)	(0.006)
Constant	0.078 ***	0.073 ***	0.062 ***	0.058 ***	0.062 ***	0.058 ***	0.053 ***
β_0	(0.008)	(0.008)	(0.008)	(0.008)	(0.008)	(0.008)	(0.008)

Notes: N = 14,520 company pairs for 177 firms. Estimation method: OLS. Robust standard errors adjusted for intragroup correlation (grouped by one company in the pair) in parentheses. Significance levels: * $0.01 < p \leq 0.05$; ** $0.001 < p \leq 0.01$; *** $p \leq 0.001$. SE = standard error.
[1] This regressor has been multiplied by 1,000 causing its coefficient to deflate.

technology proximity and industry effects remain significantly positive. Product market proximity is not significant in any of the models. Overall, the results obtained from using comovement at higher frequencies substantiate the previous findings and, furthermore, provide interesting comovement patterns regarding the regressors.

Table 33: Estimation Results (Dependent Variable: Comovement at Higher Frequencies)

Variables	Model M8a	Model M8b	Model M9a	Model M9b
Estimation method	QAP	adjusted SE	QAP	adjusted SE
Frequency of comovement	weekly	weekly	daily	daily
Time window of comovement	2 years	2 years	1 year	1 year
IP portfolios				
Technology proximity	0.044 **	0.044 ***	0.035 **	0.035 ***
β_T	[0.009]	(0.010)	[0.008]	(0.006)
Product market proximity	0.016	0.016	-0.001	-0.001
β_M	[0.259]	(0.011)	[0.536]	(0.007)
Industry-specific component				
Same industry (dummy)	0.025 **	0.025 ***	0.013	0.013 **
β_m	[0.007]	(0.006)	[0.071]	(0.005)
Control variables				
Same country (dummy)	0.075 ***	0.075 ***	0.150 ***	0.150 ***
β_c	[<0.001]	(0.008)	[<0.001]	(0.008)
MSCI-related comovement [1]	0.300 ***	0.300 ***	1.726 ***	1.726 ***
β_σ	[<0.001]	(0.025)	[<0.001]	(0.153)
Constant	0.072 ***	0.072 ***	0.029 ***	0.029 ***
β_0	[<0.001]	(0.008)	[<0.001]	(0.005)
Diagnostics				
R^2	0.350		0.549	
Log likelihood	9,900.37		13,292.75	

Notes: N = 14,520 company pairs for 177 firms. Estimation method 'QAP': 1,000 OLS estimation-based iterations. p-values in squared brackets. Estimation method 'adjusted SE': OLS estimation with robust standard errors adjusted for intragroup correlation (grouped by one company in the pair) in parentheses. Significance levels: * $0.01 < p \leq 0.05$; ** $0.001 < p \leq 0.01$; *** $p \leq 0.001$. SE = standard error.
[1] This regressor has been multiplied by 1,000 causing its coefficient to deflate.

In the third step, I use a different approach to compute the proximity measures. Recall that the measure for technology proximity, for example, is based on the activities of companies' research interests. To establish the distribution vectors for each company, the underlying technological areas were populated simply by counting the patents. However, numerous studies have argued that the value of patents, which has been found to be highly skewed, should be considered (Harhoff *et al.*, 1999; Harhoff *et al.*, 2003b). I therefore recalculated companies' technology proximity by weighting patents with the forward citations they receive to account for the distribution in patent value.[163] With trademarks, I use the number of seniorities to account for their value.[164] Accounting for the value of patents and trademarks did not alter the previously reported results substantially. The results are therefore not reported.

5.6 Conclusions

In this chapter, I have investigated different sources of comovement and, in particular, how patterns of stock movement are determined by companies' technology- and market-based assets, which I derived from companies' patent and trademark portfolios. To my knowledge, this is the first analysis that empirically explains comovement through IP portfolios in order to determine companies' activities in both the technology and the product market space. According to traditional theory, comovement of stock returns is rooted in companies' fundamentals. That is, stock returns of two companies are correlated due to a common factor in their fundamental values. This is the primary source of comovement. Alternative theories, however, suggest a secondary source and argue that comovement also occurs due to patterns in investors' trading behavior (Barberis and Shleifer, 2003; Barberis *et al.*, 2005): Categorization schemes such as industries help analysts to deal with thousands of stocks as they may simplify their decision-making processes (Mullainathan, 2002). The classification of stocks based on various categorical systems induces patterns of comovement, for example, if investors prefer specific categories (such as countries or industries) or if investors invest their funds on the category-level instead of the individual stock-level. Therefore, comovement of stock returns cannot be analyzed without considering such categorizations.

Investigating comovement in this setting is important for several reasons. In the comovement literature, fundamentals are regularly proxied by various measures derived from accounting or financial market data (e.g., Boyer, 2004; Pindyck and Rotemberg, 1993). However, these data are only the monetary results of companies' operations and, thus, should be complemented by other data that allow assessing the intangible assets owned by a company that produced these numbers. By relying on patents and trademarks, I take such an approach and assess companies' technology-

[163] Like in research where more recent studies cite previous work, later patents may cite earlier patents. Those patents that collect more citations in the following years have been found to be of higher value (e.g., Trajtenberg, 1990).

[164] When filing a CTM, an applicant may claim seniorities in his trademark application to get his previously registered trademarks continued on the pan-EU level (European Council, 1993, Art. 34, von Graevenitz, 2007).

and market-based assets by their IP portfolios. Investors seek to gather a comprehensive picture when they analyze companies and draw on categorizations of companies (e.g., industry classifications). A major distinction exists between technology and product market activities on the one hand and industries on the other hand. The industries defined by a particular industry classification scheme are, by definition, mutually exclusive. In contrast, the approach used in this analysis to determine companies' activities in the technology and product market space measures companies' similarities and, therefore, allows companies' activities to overlap. Put differently, industries are discrete whereas measures of technology and product market activities are continuous. This allows distinctions to be drawn between companies pooled in the same industry. The impact of technology and product market activities on comovement can be assessed and compared to the impact of industries. This also deepens our understanding of how financial market dynamics react to categorical systems (Zuckerman and Rao, 2004).

The results indicate that companies' technological activities, their product market positions, and their industry affiliations add value in explaining comovement even though technologies, product markets, and industries are, as demonstrated, not independent. Of these factors driving comovement in stock returns, technology and product market activities outperformed industry effects. Analyzing the relationship between technologies, product markets, and industries in greater detail revealed that companies in distinct industries may still be related in terms of technology or product market activities. Although evidence for industry-specific comovement was found, its explanative power was to a great extent absorbed by companies' technologies and product market activities. This finding is interesting as it implies that the industry-specific component of comovement may be overestimated because other, more fundamentals-based factors may actually drive comovement.

These results exhibit several features that may be interesting for both researchers and analysts. Companies' technology and product market activities were found to matter in financial markets. Patent data has often been used in research but the combination of trademarks, patents, and financial data has only rarely been explored. As companies' patent and trademark portfolios carry information about intangible assets, this information is interesting for analyzing the fundamentals of companies and comparing them on a large scale. As analysts regularly make fundamentals-based predictions about future company performance, they could employ such information to analyze companies and compare them with their competitors. Moreover, the relationship between fundamentals and comovement could help investors to select companies in which to invest because knowing the patterns of comovement can support appropriate portfolio selection to control for risk exposure and to achieve diversification (Cornell, 2004). This is of particular importance as patents informing about technological activities and trademarks informing about product market activities can both be obtained in addition to industry categorizations. For both researchers and analysts, it is empirically convenient to rely on industry categorizations because classification schemes usually provide a very powerful device for simplifying or even enabling analyses and comparisons of various objects. For financial markets, the growing importance of categorizations has been noted (Barberis and Shleifer, 2003). Despite the prevalence of categorizations, their appropriateness has been called into the question (Zuckerman and Rao, 2004). The homogeneity of companies within industries may vary, and companies affiliated with a particular industry may be more heterogeneous than the category of this industry might suggest. Scrutinizing the classification of objects by questioning *how* objects have been grouped or separated is important, especially because classification schemes are often set up for completely different purposes than those of interest to researchers or analysts.

Some limitations of this study need to be mentioned. To map companies' technology and product market activities, IP rights were used. The IP-based classifications used to identify companies' activities may, like industry classifications, be criticized as they conflate companies' very diverse profiles in technologies and product markets into a set of categories. However, the main distinction between these IP classifications, as applied in this study, and industry categories is that the IP classifications were used to build vectors containing the full distribution of companies' activities. Another limitation is that, to obtain a measure of comovement, I followed other work relying on correlation coefficients of stock returns (Zuckerman and Rao, 2004). Alternative measures of comovement in stock returns such as betas or R^2 measures (e.g., Barberis *et al.*, 2005; Roll, 1988) could also be used to substantiate the findings of this study although I do not expect the results to change in a major way.

Fruitful avenues for future research can be identified. Revealing companies' technologies and market activities with IP portfolios may be useful in examining a wide range of interesting research questions related to the valuation of companies or financial market dynamics. Using trademarks to analyze companies' market-based assets appears to be a very promising task as they can be registered for the full spectrum of products and services (Mendonça *et al.*, 2004; WIPO, 2006).[165] As both trademarks and patents inform researchers about companies' fundamentals but are not drawn from accounting or financial market data, it would be particularly interesting to use them to compare and dissect the relative importance of the traditional theory of comovement and the friction- or sentiment-based theory. Such investigations could culminate in examining the justification and appropriateness of applying different industry classifications in financial market analysis.

[165] This is in contrast to patents for which researchers are regularly required to constrain their analyses to specific sets of industries (Fung, 2003, 2006).

6 Summary of the Results and Outlook

Intangible assets such as knowledge assets or brand assets are highly important to companies. However, present accounting practices have difficulty determining the value of these intangible assets. A substantial divergence thus exists between company assets reported by accounting and the ‘real’ value of companies (i.e., their market value). This leads to the following questions: Which intangibles contribute to the value of companies? How large are their contributions? How can they be measured? The objective of this dissertation was to examine the valuation of technology- and market-based intangible assets. This was done using companies’ patent and trademark portfolios to investigate how financial markets value technology- and market-based assets. Specifically, European Patents and CTMs were considered which largely cover the same territory of European countries.

Chapter 2 described the European trademark system in order to deepen our understanding about the CTM as a pan-EU trademark right. It was described how CTMs can be registered, and which importance trademarks in general have in the course of trade. Furthermore, descriptive statistics about CTMs and CTM applicants were presented. The discussion of the European trademark system is necessary because, except for researchers engaged in studying IP law, too little is currently known about CTMs. Very few empirical studies exist that have used CTMs to study trademarks. However, this is not a CTM-specific phenomenon because research on trademarks generally is scarce. This paucity of trademark-related research is surprising when looking at the wide acceptance of CTMs. Small- and medium-sized enterprises as well as large corporations from both European and non-European countries exhibit a considerable activity of filing CTMs: Over 550,000 applications have been filed for this unitary IP right which is valid in all 27 member states of the EU. The scarcity of research on trademarks is even more surprising in light of the extensive body of other IP-related work on patents. This chapter intended to set the groundwork necessary to fill the research gaps on trademarks.

Chapter 3 examined the market value of R&D, patents, and trademarks. Previous studies have mainly focused on the valuation of knowledge assets which were either assessed by R&D investments, patents, or both. These studies regularly employed the market value approach which views a company as a bundle of both tangible and intangible assets and draws on the market value of a company, obtained from financial markets, as a forward-looking performance measure. Investors in financial markets value knowledge assets because they are required to develop and manufacture a company's products. Investors also value companies' market-based assets. Trademarks, for example, influence consumers' product choice or command price premia thereby affecting future revenue streams and, thus, the valuation of companies in financial markets. The purpose of this chapter was to jointly consider knowledge assets and trademarks in a Tobin's q framework in order to estimate their contribution to company value.

Two main implications can be drawn from the findings for both researchers and practitioners. First, both knowledge assets (either operationalized by R&D investments or by patents) and trademarks are valued by investors. However, patents were only valued if they were weighted by their citations. Thus, to obtain meaningful insights from patents, researchers have to account for their quality. Analogously, analysts who appraise companies should analyze the value of patents instead of simply counting their number. Second, because the value of trademarks also varies widely, I constructed indicators of trademark value to account for their dispersed value. I used data available in the publicly accessible trademark register to derive the following four value indicators: (i) Nice classes informing us about the breadth of trademarks, (ii) seniorities reflecting the familiarity of the consuming public with trademarks, (iii) oppositions brought against rivals indicating the intensity, with which a company protects its presumably valuable brand assets, and (iv) oppositions received from rivals reflecting third parties' honoring of the potential value of owned trademarks. Of these indicators, seniorities and oppositions brought were found to reflect trademark value. Nice classes were negatively associated with company value. Thus, they seem to measure company diversification indicating that more concentrated companies are more highly valued and, conversely, that more diversified companies receive a discount in financial markets. These trademark value indicators might be interesting for both researchers and analysts because they can be obtained on a large scale for both small- and medium-sized companies as well as for large corporations.

Chapter 4 scrutinized companies' trademark portfolios in detail and examined the trademark filing strategies that produced these portfolios. Basically, corporate brand management deals with how brands (and therefore trademarks) are attached to products. Thus, decisions within brand management include whether, in the case of introducing a new product, a new brand is created or an existing brand is re-used. Because both brand creation and brand development are reflected by trademark filings, I defined the following four trademark filing strategies: (i) creating, (ii) hedging, (iii) modernizing, and (iv) extending brands. In the case of the first strategy, brand creation, trademarks are filed because a new brand is created, for example, to cover new products. Second, trademarks that hedge brands are filed if a company simultaneously applies for several trademarks that are highly interrelated and that jointly support various facets of a brand. Third, the strategy of modernizing brands is used if trademarks are filed in order to update the appearance of a brand or to prevent an established brand from becoming obsolete. Fourth, extending brands involves trademarks that are filed if established brands are to be extended to products in familiar or unknown markets. In line with these trademark filing strategies, I developed metrics to characterize companies' trademark portfolios. I then applied the market value approach to investigate how financial markets value the benefits provided by the trademark filing strategies.

This chapter may contain valuable lessons for both researchers and practitioners. It is important for both to recognize that trademark portfolios are not loose agglomerations of independent trademarks. Instead, groups of trademarks within a portfolio exist so that the trademarks within such groups jointly protect the brands of a company. For example, it was shown that some of *Microsoft*'s brands, e.g., *Windows*, *MSN*, *Xbox*, and also the corporate brand *Microsoft*, are protected by groups of trademarks. I called these groups 'trademark families'. *Microsoft* is not a unique example since many companies hold large trademark portfolios with the inherent logic of trademark families. Revealing the structure of companies' trademark portfolios unveiled how companies built their portfolios to protect their brands. With the technique presented in this chapter, researchers and practitioners can now examine companies' brand assets in great detail. Companies' trademark portfolios are produced along different filing strategies. Investigating how financial markets value the benefits of these strategies yielded the following results: Those trademarks that were filed in order to modernize or to extend existing brands were found to be valued in financial markets. This finding was explained by the cash flow generating potential of these strategies. By modernizing strategies, companies protect their established brands against impairment so that future product introductions can benefit from these brands. Moreover, only strong brands provide powerful platforms for future extensions. In the case of extending brands, an established brand is leveraged to familiar or new markets allowing a company to tap into consumers' previous experiences with a brand. This increases the potential success of new products while benefiting from advertising efficiencies. It is important for both researchers and practitioners to understand that financial markets do not value arbitrary filings of any trademarks. Instead, the gradual development of brands is valued implemented by the systematic filing of new trademarks so that, first, the appearance of established brands is continually kept up-to-date and, second, the reputation of existing brands can be leveraged when new products are introduced.

Chapter 5 examined how both technology- and market-based assets drive patterns of stock movement. While the Tobin's q framework used in Chapter 3 and Chapter 4 allowed assessing the valuation of intangibles at discrete points in time, the approach chosen in this chapter examined continuous patterns of stock movement based on monthly, weekly, and even daily observations of stock prices. More specifically, I formed pairs of companies and assessed the comovement of their stocks, i.e., the degree of synchronous movements within each pair of stocks. In theory, the primary source of stock comovement is that companies' fundamentals are correlated. Then, company values in financial markets change symmetrically. To assess companies' technology- and market-based assets, proximity measures were computed for each company pair based on their patent and trademark portfolios. Accounting for an industry-specific component of stock comovement, it was then analyzed which impact technology and market proximity had in explaining the comovement of stock returns.

The results of this chapter have important implications for researchers and practitioners. Because investors in financial markets constantly appraise investment opportunities, insights into the factors that drive stock comovement can help investors with optimizing their portfolio selection to control for risk exposure and to achieve diversification. It was found that both technology and market proximity were important factors in explaining comovement of stock returns. Industry-specific comovement could also be observed but its explanatory power was partially absorbed by the technology- and market-related variables. This is interesting for both researchers and analysts because industry classifications can and should be complemented by other data such as IP portfolios that appropriately reflect companies' intangible assets. While industry classifications separate companies into discrete categories, the technology and market-related variables used in this chapter provide continuous measures to assess companies' intangibles. These measures allow researchers and analysts to carve out differences between companies within the same industry or assess similarities between comparable companies in different industries.

Two main avenues for future research on intangible assets, patents, and trademarks can be identified. First, the relationship between different kinds of IP rights requires further inquiry. Patents protect the technological base that allows companies to develop and manufacture their products. If these products are sold to consumers, trademarks are attached to transmit information. Some researchers expect patents and trademarks to be highly related. Similarly, trademarks have been proposed as an indicator of innovation. To what degree these suggestions hold, if at all, would be an interesting research question. Studying the relationship between R&D and marketing activities might be challenging but demands further attention. When taking on this challenge, the valuation of companies in financial markets could again be used as an external evaluation of company performance.

Second, it is also important to investigate how companies back their brands with trademarks and how they assign brands and trademarks to products. Brands can be represented by bundles of trademarks. Over time, companies develop brands further so that, in some cases, a brand may even outlive the company that originally created it. Investigating why companies invest in brand assets and how companies further develop their established brands seems to be a promising field of future research, especially because trademarks allow researchers to analyze the entire brand portfolios of companies. This field of research is interesting because brands are intangible assets that can be virtually indefinitely deployed to new products in both familiar and unknown markets. Assessing the allocation of brands to products, including the dynamics over time, might yield interesting results. Recall that trademarks can be registered for the full range of manufactured goods and services. Thus, these analyses would not necessarily have to be restricted to specific industries. To examine the relationship between trademarks, brands, and products, financial markets' expectations about future firm performance could again be used. In general, investigating intangible assets by drawing on IP data to assess technology- and market-based intangibles provides numerous opportunities for future inquiry. Considering this broad array of research agendas, this dissertation may have provided valuable insights to conduct future research projects.

Appendix: Connecting Companies with Patent and Trademark Applicants

To build consistent IP portfolios at the corporate level, trademarks and patents of each firm must be consolidated. The OHIM database and PATSTAT provide very similar structures regarding their raw data. Both data sources include lists of applicants. The OHIM database contains a list of trademark applicants whereas PATSTAT provides a list of patent applicants. The list of trademark applicants allows one to trace, for example, registered trademarks or lodged oppositions. Correspondingly, the list of patent applicants may be used to investigate applicants' patent activity. Each list provides an applicant identification number which provides full consistency *within* its database, but there is no straightforward way to build a link *between* both databases.

It is important to note that a company as a corporate entity may be represented by a broad array of applicants.[166] This can be explained in two ways. First, a single corporate entity may comprise different legal entities.[167] This may be due to the structure of subsidiaries concerning business segments and international operations. Regarding the data, all legal entities act as separate applicants with different names. Second, during the process of trademark or patent application, misspellings or slight variations in applicants' names immediately lead to several records thereby spuriously inflating applicant lists (Magerman *et al.*, 2006).

An algorithm was employed to address this issue. This algorithm starts with a given set of companies and assigns all trademarks and all patents to the appropriate corporate entity according to given rules. More specifically, an IP portfolio made up by a trademark layer drawn from OHIM data and a patent layer obtained from PATSTAT is built for each of the firms in the sample. Due to the structural similarity of the data

[166] For example, in the OHIM database, *Nokia* comprises 11 different applicants. *BASF* is represented by 23 applicants.

[167] The applicant name refers to the full legal notation of a legal entity. Thus, *Siemens AG* is different from *Siemens plc, Siemens Ltd.*, or *Siemens NV.*

sources, this algorithm can be applied to both of them. First, all trademark applicants are connected to the firms in the sample, followed by all patent applicants.

The algorithm is set up in three steps: (i) name cleaning, (ii) name matching, and (iii) treatment of multiple applicants. Regarding the first step, applicant lists are cleaned using routines provided by Bronwyn Hall. This, for example, unifies *I.B.M.* into *IBM.* Trademarks and patents were treated symmetrically. This step solves a substantial share of problems; however, consolidation of unified applicant names is not sufficient as there are numerous variations in the names of legal entities.

The second step consolidates the various appropriate applicants to one corporate entity by employing a strategy termed 'search engine logic'. Once again, the same criteria are used for both sets of raw data. This approach rests on a simple thought: the name of each company contains an idiosyncratic part that can potentially distinguish it from other firms.[168] If individuals seek information about a company, they use this identifying pattern to collect information. In the case of *Motorola, Inc.*, this is neither the full legal name nor the fragment *Inc.*, but simply *Motorola*. Within the legal notation *Siemens AG*, *Siemens* is the idiosyncratic part and not the legal form *AG*. If a company name is composed of multiple words, the specific pattern may also need to be composed of several words. This category is illustrated by *Analog Devices, Inc*. Neither *Analog* nor *Devices* is idiosyncratic, but the combination *Analog Devices* is sufficient. To account for misspellings or abbreviated notations of applicants, truncated patterns were developed for potentially affected companies. For *Sun Microsystems, Inc.*, the pattern *Sun Microsys** was employed with the asterisk indicating an arbitrary continuance of that name. Thus, this pattern recognizes the misspelled name *Sun Microsystem* as well as the correct name *Sun Microsystems*.[169] A yet more complex situation arises when abbreviations of companies are common. Here, the abbreviated name might be used with the same frequency as the unabbreviated name. Consequently, such corporate entities are represented by multiple patterns. Examples of this kind include *General Electric* or *IBM.* These examples show that both the unabbreviated names (*General Electric*, *International Business Machines*) and the abbreviated ones (*GE*, *IBM*)

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168 Similar approaches have been used, for example, by von Graevenitz *et al.* (2008).

169 These patterns are not capable of considering all misspellings in applicant names. To address this problem, similarity measures as demonstrated by Cohen *et al.* (2003) need to be used. Such measures produce pairwise propensity scores for a set of names. Applying such methods results in a complete new array of challenges, for example, determining the minimum thresholds beyond which identity of applicants is assumed. Low thresholds lead to the problem that completely different entities are lumped together if they show a sufficiently high similarity score. Conversely, high thresholds lead to a low matching rate.

are valid patterns. In particular, the latter examples show that an automatic generation of search patterns will lead to deception. Therefore, the idiosyncratic patterns were manually established for 4,085 firms. For each company name, I replicated the identifying word or the combination of words needed to retrieve an undistorted set of information about the specific company. If required by virtue of the company name, multiple idiosyncratic patterns were created. All together, 4,594 search patterns were used of which 3,618 firms had one pattern (89.8%). The whole set of search patterns was applied to the trademark and the patent applicant lists. Ownership and name changes pose difficult issues regarding the consolidation of trademarks and patents. For the purpose of this dissertation, I only dealt with major ownership and names changes.[170] Of course, more complex issues arise from acquisitions or mergers; these issues are deferred to future research.

The third step of the algorithm concerns the treatment of multiple applicants. This issue appears in two variations. The first issue only regards patents since a single patent may involve a group of applicants. This issue is irrelevant for trademarks since only one applicant is allowed per trademark application. The second issue stems from the possibility that several name patterns may be found within *one* applicant name. Regarding the first issue, multiple patent applicants appear in only 5% of all European Patents. Fractional counting was applied, assuming that the economic interests are uniformly distributed. If a patent is jointly held by three applicants, one third of this patent will be allocated to each of the three applicants. If, when applying the idiosyncratic name patterns, only two of the applicants were recognized, the whole patent is considered as two thirds of a whole, of which one third is allocated to each of the two recognized applicants. The remaining third, which would be allocated to the unrecognized applicant, is disregarded. The second issue concerns multiple patterns within *one* applicant name. The data indicated that this constellation appears to a large extent if companies form joint ventures (e.g., *Siemens Fujitsu*, *LG Philips*, *NEC Hitachi Memory*, *GE Bayer Silicone*, or *Sony Ericsson*). In each of these examples, two company patterns (e.g., *Siemens* and *Fujitsu*) are found within a single applicant name. The existence of joint ventures as legal entities precludes knowledge of the extent to which the participating companies exploit the IP rights owned by the joint venture. Furthermore, assuming equal distributions of ownership shares may not reflect reality. Thus,

[170] For example, the former name of *3M Company* was *Minnesota Mining and Manufacturing Company*. This name change required the development of multiple patterns to recognize corresponding applicants. To illustrate the need for additional patterns due to ownership changes, two of the acquisitions considered are *Westinghouse Electric Company* (acquired by *Toshiba*) and *Hughes Aircraft* (bought by *General Motors*).

the connections to corporate entities were simply removed and the trademark or the patent was not assigned to any corporate entity. These cases only represent 1.2% of all allocated trademarks or 1.5% of all allocated patents. Thus, it is rather unlikely that this treatment affects the results in a major way.

At the outcome stage of the algorithm described above, 35,184 of the 229,627 registered CTM applications in the OHIM dataset were allocated to corporate entities accounting for 15.3% of all CTM applications. Regarding all European Patents available in PATSTAT, 436,677 of the 864,980 patents were assigned to companies corresponding to 50.5% of all European Patents. It is interesting to note that the ownership of patents is substantially more concentrated than that of trademarks. This indicates that trademarks are registrable for a wider set of industries and that small and medium-sized enterprises are more likely to register trademarks due to lower barriers and lower registration costs. Table A1 lists the 30 companies with the largest trademark portfolios.

Table A1: Matching Results for Companies with the Largest Trademark Portfolios

Nr	Company name	CTMs	European Patents
1	The Procter & Gamble Co.	668	3,541
2	Konami Corp.	616	159
3	DaimlerChrysler AG	616	2,270
4	BASF AG	558	13,043
5	Deutsche Telekom AG	546	266
6	GlaxoSmithKline plc	387	1,446
7	Sony Corp.	369	5,698
8	Pfizer Inc.	367	2,709
9	Novartis AG	339	1,122
10	Syngenta AG	315	336
11	L’Oréal	314	2,276
12	Microsoft Corp.	281	397
13	International Business Machines Corp.	274	8,364
14	General Electric Co.	258	4,420
15	Unilever NV	243	2,817
16	Bayerische Motoren Werke AG	239	1,739
17	Hewlett-Packard Co.	236	3,286
18	Eli Lilly Co.	218	1,053
19	Bayer AG	216	8,628
20	Viacom, Inc.	211	0
21	Volkswagen AG	209	1,140
22	Altana AG	208	104
23	Diageo plc	198	1
24	Schering-Plough Corp.	192	1,262
25	Bristol Myers Squibb Co.	188	528
26	Exxon Mobil Corp.	186	3,126
27	Sanofi Aventis	185	6,836
28	Abbott Laboratories	184	901
29	Baxter International Inc.	181	858
30	Saint-Gobain SA	178	1,477

Notes: Descending order by number of CTMs. Fractional counting for European Patents was applied.

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