

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

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Abstract

The purpose of paper is to investigate the contribution of R&D investments, patents, and trademarks to the market valuations of companies using a Tobin's q format. I employ non-linear least squares (NLLS) regression techniques to estimate the market valuation equation for 6,757 observations in the years 1996 to 2002. The results show that trademarks, which have rarely been examined in previous research, play an important role in determining company valuations. 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.

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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 higher market valuations in the financial market (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, but 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 brand assets.

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 two 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). This latter

requirement guarantees that common words are inherently unregistrable because they are devoid of distinctive character (European Council, 1993, Art. 7).² Moreover, 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). 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. Thus, trademark rights 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.³ 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 through, for example, counterfeiting or imitation. Consequently, trademark rights can be viewed as legal anchors of brands. The importance of trademarks is also documented in the immense number of trademark applications in Europe.⁴ At the end of 2007, over 640,000 CTM

² Thus, the word *Apple* does not qualify for registration as applied to fruits because it lacks distinctiveness with regard to this product category. Yet, it is eligible for protection when used for computers.

³ Within the field of business administration, a large body of literature discusses the use of trademarks 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.

⁴ The CTM is valid in all member states of the EU. The CTM system was established by 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.

applications had been filed with the OHIM. Of these applications, 420,000 became registered as CTMs (OHIM, 2007).

The objective of this study 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 reflecting trademark value; these indicators are obtained from publicly available trademark data and can thus be widely applied. They are: (i) Nice classes, which inform us about the breadth of trademarks, (ii) seniorities, which reflect the familiarity of the consuming public with trademarks, (iii) oppositions brought against rivals, which indicate the intensity of a company's protection of its trademarks, and (iv) oppositions received by rivals, which reflect 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 show 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? Second, which indicators of trademark value, similar to patent value indicators, can 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 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 ac-

counting and financial data, firm-level IP portfolios, comprising both trademarks and patents, are constructed. The IP rights considered in these portfolios are European Patents issued by the EPO and CTMs granted by the OHIM. European Patents and CTMs cover roughly the same geographical area. Trademark data, in particular CTMs, have very rarely been employed in the analysis of firms' market valuations, compared to accounting, financial, and patent data. Regarding patents, citations were used to account for their greatly dispersed 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 since they are positively associated with firm value. Although both measures of knowledge assets, investments in R&D and patents, were positively associated with Tobin's q , it was found, however, 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 add further value, as is 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 reflected in trademarks' seniorities. Finally, companies that defend their trademark portfolio more vigorously are more highly valued. This renders trademark oppositions economically relevant and shows that an active management of trademark portfolios is valued. 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 the study is divided into four sections. Section 2 presents the market value approach. Drawing on previous studies on the market valuation of knowledge assets and trademarks, it also describes the method used to estimate the economic value

of knowledge assets and trademarks using financial data. Section 3 presents the data and describes the variables while Section 0 reports the results of estimating the market value equation. Finally, Section 5 provides a conclusion that addresses the limitations of this study and indicates avenues for future research.

2 Trademarks and the Market Value Approach

This section describes the market value approach (Section 2.1) and discusses how trademarks are accommodated in the market value equation (Section 2.2). Four indicators are presented to account for the great dispersion in trademark value (Section 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 2.4). Finally, I highlight issues related to the estimation of the model (Section 2.5).

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.⁵ 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 of 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. 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 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

⁵ An analytical evaluation of econometric approaches to assessing the economic value of R&D is presented by Hall (2007).

Griliches (1981), the typical linear market value model assumes that firms' assets enter the market value equation additively:

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

with

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

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, 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 nor demand of 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 the values of patents (Hall *et al.*, 2005).

Note that all assets are stock variables (as opposed to flow variables).⁶ 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%.

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, which should be incorporated in q_{it} . Hirsch

⁶ 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).

and Seaks (1993) highlighted measures of market structures. Trademarks protect companies' assets from erosion and allow their owners to defend their brands 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. 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 means to protect IP are treated in an analogous way to knowledge assets. Therefore, the market value equation

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

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

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

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.

2.3 Indicators of Trademark Value

The value of patents has 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 goodwill⁷ (Phillips, 2003; Smith, 1997). 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 seniorities, oppositions lodged against others, and oppositions received by rivals. With the exception of von Graevenitz (2007), who points 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 1 summarizes these insights. Where possible, a comparison to patents is drawn because value indicators of patents have been intensively discussed in the literature.

⁷ 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.

Table 1: 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	<ul style="list-style-type: none"> - Breadth regarding goods and services covered 	<ul style="list-style-type: none"> - Scope of technological classes - Claims 	Lerner (1994); Harhoff and Hall (2003)	Firm, trademark
Seniorities claimed	<ul style="list-style-type: none"> - Familiarity and diffusion due to previously existing trademarks - Reflecting potential awareness 	<ul style="list-style-type: none"> - Geographical coverage as measured by the size of patent families - Targeted markets 	Putnam (1996)	Firm, trademark
Oppositions brought by an applicant	<ul style="list-style-type: none"> - Monitoring activity and capability of perceiving threats - Protection of own assets, degree of aggressiveness and willingness to damage others 	<ul style="list-style-type: none"> - Monitoring activity and capability of perceiving threats - Protection of own assets, degree of aggressiveness and willingness to damage others 	Harhoff <i>et al.</i> (2003a)	Firm
Oppositions received by a trademark application	<ul style="list-style-type: none"> - Being recognized and monitored - Being a potential threat to competitors or other firms - Owning potentially valuable assets 	<ul style="list-style-type: none"> - Being recognized and monitored - Being a potential threat to competitors or other firms - Owning potentially valuable assets 	Harhoff <i>et al.</i> (2003a)	Firm, trademark

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 services classes. Assessing trademarks' subject matter reveals that those applied for only a 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).⁸ The classes are set out by the Nice Classification and span 34 goods and 11 service classes (WIPO, 2006). 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 of the subject matter 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. There-

⁸ A brand can be said to be an umbrella brand, if it spans several products (Erdem, 1998; Wernerfelt, 1988).

fore, 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 registrations 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.⁹ However, since seniorities capture only earlier trademark rights, this value indicator is biased when applicants file 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

⁹ 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.

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).¹⁰ If successfully opposed, this attacked trademark application is rejected. Oppositions involve 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 by 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

¹⁰ An opposition can be lodged within three months following the publication of a CTM application (European Council, 1993, Art. 42).

lead rivals to oppose them. Hence, it is expected that, *ceteris paribus*, the more oppositions a trademark attracts, the higher its potential value.

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 trademarks' values in the market equation is similar to that employed by Hall *et al.* (2005), who use citations as an indicator of patent value and 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 by 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 received 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 Equation 5:

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

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 was 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 (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 , accounting for non-linearity.

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 3.1). It also discusses the variables that enter the empirical model (Section 3.2) and presents descriptive statistics (Section 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.¹¹ Trademark data were provided by von Graevenitz (2007), who obtained the source files from the OHIM's CTM register. For patent data, the worldwide patent database PATSTAT was used.¹² 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.¹³ 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 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, and 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.¹⁴

CTMs were extracted from the OHIM database and European Patents from PATSTAT in order to build firm-level IP portfolios. 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 processed increases with later cohorts, the

¹¹ More specifically, I used the GlobalVantage database, which is the license covering international data within the Compustat database provided by Standard & Poor's.

¹² 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.

¹³ 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).

¹⁴ Website: http://ec.europa.eu/economy_finance/db_indicators/db_indicators8646_en.htm (accessed on February 13, 2008).

number of registered CTMs, in particular for the 2003 and 2004 cohorts, drastically decreases. Since this study 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.

For the years 1996 through 2002, patents and trademarks were consolidated on the corporate level.¹⁵ 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 study 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.¹⁶ This trimming reduced the data to 1,232 companies (7,081 observations). Finally, observations with extreme outliers were excluded.¹⁷ The final dataset consisted of 6,757 observations for 1,216 publicly traded firms. It is 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).¹⁸

3.2 Variables

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

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

¹⁵ Recall that the OHIM commenced its operations in 1996 so that no CTMs could be filed previous to that year.

¹⁶ 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).

¹⁷ 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.

¹⁸ 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.

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.¹⁹

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.²⁰ 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.²¹

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 normally 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, a so-called declining balance formula with a constant depreciation rate, δ , is regularly employed, relying on present and past R&D

¹⁹ The corresponding Compustat item is AT .

²⁰ The Compustat item $MKVAL$ is the product of the number of outstanding shares ($CSHO$) and the closing price of each period ($PRCCM$).

²¹ 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 $(PRCCM \cdot CSHO + DT)/AT$.

flows²² (e.g., Hall and Oriani, 2006; Hall *et al.*, 2005; Hall *et al.*, 2007).²³ Following other work, a usual depreciation rate of 15% was used to reflect obsolescence of investments in R&D (Hall, 2007):

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

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:

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

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.²⁴ 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., 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:

²² R&D flows equal R&D expenditures. They are drawn from companies' annual income statements and captured by the Compustat item *XRD*.

²³ For details regarding the declining balance formula see Hall (1990).

²⁴ 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.

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

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.²⁵ 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 enters a company's patent portfolio is weighted with the number of its forward citations. The resulting citation stock is computed according to:

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

²⁵ The earliest priority application is the first time a patent application of the underlying invention appears in world-wide 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.

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:

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

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.

3.2.4 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 4 in Section 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 Descriptive Statistics

Table 2 sets out descriptive statistics for the 6,757 observations of the final dataset. If only the most recently available observation for each company was used, Table 3 reports 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 here, I refer to Table 2 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.²⁶ 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 that takes the value one if no R&D data are available. This was the case for 40.9% of all observations.²⁷ The average ratio of R&D stock to assets is 0.169. The same practice

²⁶ The maximum value of assets belongs to *General Electric*.

²⁷ Descriptive statistics for both R&D stock and R&D stock / assets were computed conditional on R&D availability.

Table 2: 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		0.0	0.0	1.0
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	0.0	0.677
No patents (dummy)	0.213		0.0	0.0	1.0
Patent stock ²	149.191	386.907	27.138	0.064	5,431.082
Patent stock / assets ²	0.025	0.053	0.010	0.0	1.481
Citation stock ²	134.181	350.074	20.114	0.0	3,500.318
Citation stock / assets ²	0.019	0.043	0.005	0.0	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		0.000	0.000	1.000
Japan	0.226		0.000	0.000	1.000
UK	0.073		0.000	0.000	1.000
Germany	0.052		0.000	0.000	1.000
France	0.046		0.000	0.000	1.000
Italy	0.020		0.000	0.000	1.000
Canada	0.016		0.000	0.000	1.000
Korea	0.013		0.000	0.000	1.000
Switzerland	0.023		0.000	0.000	1.000
Sweden	0.023		0.000	0.000	1.000
Other countries	0.142		0.000	0.000	1.000
Years					
1996	0.126		0.000	0.000	1.000
1997	0.136		0.000	0.000	1.000
1998	0.143		0.000	0.000	1.000
1999	0.150		0.000	0.000	1.000
2000	0.159		0.000	0.000	1.000
2001	0.154		0.000	0.000	1.000
2002	0.133		0.000	0.000	1.000

Note: N = 6,757 observations. SD = Standard deviation. CTM = Community trademark.

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, have been excluded. R&D is available for 3,991 and patents for 5,318 observations.

Table 3: Descriptive Statistics of 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		0.000	0.000	1.000
Japan	0.198		0.000	0.000	1.000
UK	0.076		0.000	0.000	1.000
Germany	0.050		0.000	0.000	1.000
France	0.045		0.000	0.000	1.000
Italy	0.023		0.000	0.000	1.000
Canada	0.017		0.000	0.000	1.000
Korea	0.014		0.000	0.000	1.000
Switzerland	0.021		0.000	0.000	1.000
Sweden	0.024		0.000	0.000	1.000
Other countries	0.161		0.000	0.000	1.000

Note: 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. CTM = Community trademark.

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, have been excluded. R&D is available for 736 companies and patents for 921 companies.

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.²⁸

Table 2 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 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 received, however, reveals that

²⁸ This patent portfolio belongs to *Siemens*.

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.²⁹

Although the companies in the sample were required to be publicly traded, all trademark measures are consistent when compared with applicants in the full OHIM dataset. Table 2 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 4 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 'services' and 'biotechnology and pharmaceuticals'. 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, 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

²⁹ Recall that oppositions are outcomes of current rivalry, in contrast to seniorities, which are outcomes of companies' past trademark activities.

Table 4: Industry Characteristics

Industry	Obs.	In %	Firms	Ø total assets (million Euros) ¹	Ø Tobin's q	Ø trade-marks	% failed appln.	Per registered CTM			
								Nice classes	Senior-ities	Oppositions	
										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

Note: N = 6,757 observations. CTM = Community trademark.

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

Table 5: 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 ^{***}

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

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 6: 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

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

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 5). Correlation coefficients of high magnitude were not observed. To evaluate potential multicollinearity, the variance inflation factors were calculated. Table 6 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.

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

$$q_{it} = \exp(\rho z_{it} + \delta_{1t} d_{1it} + \delta_{2k} d_{2ik} + \delta_{3l} d_{3il} + \delta_0 + \varepsilon_{it}).^{30} \quad (12)$$

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’ regressions³¹ to show the explanatory power of knowledge assets or 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. Addition-

³⁰ Note that the individual disturbance term (Equation 2), u_{it} , is represented by the constant, δ_0 , and the error term, ε_{it} .

³¹ This term was coined by Hall *et al.* (2005).

ally, 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., regressors d_{lit} , d_{2ik} , and d_{3il} , respectively). Each set of dummy variables is jointly significant. 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 7. Model M0 (i.e., the baseline model) does not include knowledge assets or trademark stocks. The coefficient of $\log(\text{assets})$ 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 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 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 elastic-

ity 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 or trademark stocks, R^2 is considered. Compared to the baseline specification M0, this measure increases 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 were included (Model M4), the R^2 was 0.304, the highest R^2 value reported so far.

Table 7: ‘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) ($\sigma - 1$)	-0.0107 * (0.0047)	-0.0155 ** (0.0047)	-0.0073 (0.0048)	-0.0083 (0.0047)	0.0118 * (0.0051)
R&D stock / assets λ_K		0.6334 *** (0.0900)			
Patent stock / assets λ_K			0.4691 ** (0.1815)		
Citation stock / assets λ_K				1.9923 *** (0.2805)	
CTM stock / assets λ_M					14.8287 *** (1.5238)
Control variables					
No R&D ρ		-0.0055 (0.0192)			
No patents ρ			0.0706 ** (0.0197)	0.0791 *** (0.0196)	
Year dummies	Yes	Yes	Yes	Yes	Yes
Country dummies	Yes	Yes	Yes	Yes	Yes
Industry dummies	Yes	Yes	Yes	Yes	Yes
Constant δ_0	0.4304 *** (0.0483)	0.3305 *** (0.0513)	0.3875 *** (0.0493)	0.3702 *** (0.0488)	0.1491 ** (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) Compared model		87.43 *** M0	17.62 *** M0	72.16 *** M0	124.81 *** M0
Elasticities $\partial \log(V/A) / \partial \log X$					
R&D stock / assets λ_K		0.0594 *** (0.0080)			
Patent stock / assets λ_K			0.0090 ** (0.0034)		
Citation stock / assets λ_K				0.0291 *** (0.0040)	
CTM stock / assets λ_M					0.0586 *** (0.0057)

Note: 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.

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 8 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 8. 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 8, the coefficients for trademark stocks are strongly significant and positive (13.878, $p < 0.001$ in Model M1a). This supports the evidence provided in 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' regression 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.

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

Table 8: 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) ($\sigma - 1$)	0.0053 (0.0051)	0.0026 (0.0053)	0.0146** (0.0051)	0.0122* (0.0053)	0.0125* (0.0051)	0.0103 (0.0053)
R&D stock / assets λ_K	0.5337*** (0.0906)	0.5409*** (0.0910)				
Patent stock / assets λ_K			0.2479 (0.1770)	0.2303 (0.1748)		
Citation stock / assets λ_K					1.6514*** (0.2811)	1.5960*** (0.2798)
CTM stock / assets λ_M	13.8781*** (1.5505)	13.2483*** (1.5432)	14.7066*** (1.5306)	14.1260*** (1.5197)	13.7485*** (1.5263)	13.2393*** (1.5174)
Nice class stock / TM stock ξ_1		-0.0059 (0.0032)		-0.0066* (0.0031)		-0.0063* (0.0031)
Seniority stock / TM stock ξ_2		0.0083** (0.0028)		0.0077** (0.0026)		0.0078** (0.0027)
Opposition brought stock / TM stock ξ_3		0.1218* (0.0484)		0.1219** (0.0465)		0.1123* (0.0473)
Opposition received stock / TM stock ξ_4		0.0204 (0.0151)		0.0175 (0.0146)		0.0186 (0.0147)
Control variables						
No R&D ρ	-0.0175 (0.0189)	-0.0149 (0.0189)				
No patents ρ			0.0680** (0.0195)	0.0697** (0.0196)	0.0759*** (0.0195)	0.0773*** (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 δ_0	0.0979 (0.0563)	0.1178* (0.0566)	0.1179* (0.0549)	0.1396* (0.0552)	0.1175* (0.0547)	0.1368* (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· Δ (Log likelihood) Compared model	101.87*** M1	123.33*** M1	120.38*** M2	142.37*** M2	104.12*** M3	124.03*** M3
Elasticities $\partial \log(V/A) / \partial \log X$						
R&D stock / assets λ_K	0.0479*** (0.0078)	0.0483*** (0.0077)				
Patent stock / assets λ_K			0.0045 (0.0032)	0.0041 (0.0032)		
Citation stock / assets λ_K					0.0230*** (0.0038)	0.0222*** (0.0038)
CTM stock / assets λ_M	0.0524*** (0.0056)	0.0498*** (0.0056)	0.0579*** (0.0057)	0.0556*** (0.0057)	0.0533*** (0.0056)	0.0513*** (0.0056)
Nice class stock / TM stock ξ_1		-0.0124 (0.0068)		-0.0145* (0.0068)		-0.0136* (0.0067)
Seniority stock / TM stock ξ_2		0.0089** (0.0029)		0.0087** (0.0030)		0.0086** (0.0030)
Opposition brought stock / TM stock ξ_3		0.0043* (0.0017)		0.0045** (0.0017)		0.0041* (0.0017)
Opposition received stock / TM stock ξ_4		0.0046 (0.0034)		0.0041 (0.0034)		0.0043 (0.0034)

Note: 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.

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 stock valuation 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' lodging of oppositions against rivals. This can be primarily explained by firms' efforts to actively protect 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.³² 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 are informative about their value (Harhoff *et al.*, 2003a).

The coefficient of $\log(\text{assets})$ 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 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

³² Although a causal relationship cannot be taken for granted, companies' engagement in such activities is likely to prevent their assets from impairment, thus, influencing investors' assessment of their market value.

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:

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

and

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

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 $E[q_{it}] = E[\exp(d_t + c_k + m_t + u_{it})]$ and $E[q_{it}] = E[\exp(d_t + c_k + m_t)]E[\exp(u_{it})]$. According to Wooldridge (2003, p. 208), the expectation of $\exp(u)$, $E[\exp(u)]$, 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 $\hat{Q} = \exp(\hat{\sigma}^2/2)\exp(\hat{\log} Q)$. Here, $\hat{\log} Q$ 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 $\exp(d_t + c_k + m_t)$. 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 9 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 9). Note that these values are sensitive to the depreciation rates used in the stock variables’ computations. Accordingly, these calculations should be cautiously interpreted.

Table 9: Market Value of Knowledge Assets and Trademark Portfolios

Equation	Computation	Independent variables			Dependent variable		
		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.³³ Conversely, if R&D stocks are doubled, the market value increase is 200.6 million Euros. For Equation 14, where value-adjusted patent stocks proxy knowledge assets, the same increase of 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 value in relation to enterprise value. For these brands, the median share equals 14.0%, but this median share is likely to be upward biased because only the world's 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.

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 com-

³³ Similarly, a zero trademark stock, *ceteris paribus*, corresponds to a market value decrease of the same magnitude.

pared to the extensive body of literature on patents (Mendonça *et al.*, 2004). Only few studies have analyzed these intangibles jointly (Greenhalgh and Rogers, 2006a, 2006b). This study 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 the values 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 are of interest to 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 infor-

mation 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 trademarks' value; they reflect the diffusion of trademarks and consumers' potential awareness of them. Third, trademarks are more highly valued if their owners protect them more vigorously by 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 by 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. Importantly, 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 informative 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 building 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.

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 raw data. Both data sources include lists of applicants. OHIM data contain 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.³⁴ This can be explained in two ways. First, a single corporate entity may comprise different legal entities.³⁵ 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 the applicants' names will 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 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 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 were cleaned

³⁴ For example, in the OHIM database, *Nokia* comprises 11 different applicants. *BASF* is represented by 23 applicants.

³⁵ The applicant name refers to the full legal notation of a legal entity. Thus, *Siemens AG* is different from *Siemens plc*, *Siemens Ltd.* and *Siemens NV*.

using routines provided by Bronwyn Hall. This unifies *I.B.M.* with *IBM*, for example. 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.³⁶ If individuals seek information about a company, they use this identifying pattern to collect information. In the case of *Motorola, Inc.*, this 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*.³⁷ 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*) 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 the selected 4,085 firms. For each company name, I replicated the

³⁶ Similar approaches have been used by, for example, von Graevenitz *et al.* (2008).

³⁷ 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.

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 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.³⁸ 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 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 5.0% 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 participating companies will exploit the IP rights owned by the joint venture. Furthermore, assuming equal distributions of ownership shares may not reflect reality. Thus, the connections to corporate entities were simply removed and the trademark or patent was not assigned to

³⁸ 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*).

a corporate entity. Most importantly, these cases represent only 1.2% of all allocated trademarks and only 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 PAT-STAT, 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'Oreal	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

Note: Descending order by number of CTMs. Fractional counting for European Patents was applied.
CTM = Community trademark.

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