The market value of patents and R&D: Evidence from European firms

Bronwyn H. Hall*
*University of California at Berkeley, University of Maastricht, NBER, and IFS London

Grid Thoma**
** Department of Political Science and Law Studies, University of Camerino, Camerino and CESPRI, Bocconi University

Salvatore Torrisi***
*** Department of Management, Bologna University, Bologna, and CESPRI, Bocconi University, Milan[1]

DRAFT: October 30, 2006

Abstract

This paper provides novel empirical evidence on the private value of patents and R&D. We analyze an unbalanced sample of firms from five EU countries - France, Germany, Switzerland, Sweden and the UK in the period 1985-2005. We explore the relationship between firm's stock market value and patents, accounting for the 'quality' of EPO patents. We find that Tobin's q is positively and significantly associated with R&D and patent stocks. In contrast to results for the U.S., forward citations do not add information beyond that in patents. However, the composite quality indicator based on backward citations, forward citations and the number of technical fields covered by the patent is informative for value.

Software patents account for a rising share of total patents in the EPO. Moreover, some scholars of innovation and intellectual property rights argue that software and business methods patents on average are of poor quality and that these patents are applied for merely to build portfolios rather than for protection of real inventions. We therefore tested for the impact of software patents on the market value of the firm and did not find any significant effect, in contrast to results for the United States. However, in Europe, such patents are highly concentrated, with 90 per cent of the software patents in our sample held by just 15 of the firms.

JEL classification: D24, O31, O34, L86

Keywords: market valuation, intangible assets, patents, software

Acknowledgements: We thank Rishab Ghosh and the participants in the EC DG IT study on "The effects of allowing patents claims for computer-implemented inventions" for discussing with us several issues concerning patents and IPR. Moreover, we would like to thank Armando Benincasa from Bureau Van Dijk, Elvio Ciccardini, and Gianluca Tarasconi from CESPRI - Bocconi University for their valuable assistance in data collection. The usual disclaimers apply.

[1] Corresponding author: e-mail: torrisi@unibo.it

The market value of patents and R&D: Evidence from European firms

Bronwyn H. Hall, Grid Thoma, and Salvatore Torrisi

October 2006

1. Introduction

This paper provides novel empirical evidence on the private value of patents and R&D in Europe. A large body of studies have addressed this issue, mostly focusing on US data and drawing on a variety of methodologies. Traditionally, the impact of R&D and patenting on firm performance has been examined by focusing on profit or production function estimation (e.g., Norsworthy and Jang 1992; Hall and Mairesse 1995). Other studies have relied on market value estimation which is more forward looking, but requires data on the firm's value from public financial markets (e.g., see Hall, 1993). These studies use different measures of technological activity such as R&D expenditures and patent counts. More sophisticated indicators of technological assets such as citations have also been tried by the literature to account for the great dispersion in the value distribution of patents (Griliches, 1981; Griliches *et al.* 1991; Hall, 1993 and 1999; Hall *et al.* 2005; Lanjouw and Schankerman 2004). In the absence of more direct measures of the economic value of patents, these studies provide a useful methodological setting to explore the technological importance and profitability of patented inventions. Other studies which have compared measures of patent value like citations with survey-based direct measures of patent value have found a positive and significant association between them (Harhoff *et al.* 1999). More recently, Gambardella *et al.* (2005) have adopted the same approach with a survey of European inventors and found similar results. However, to our knowledge, there are only few studies focusing on European firms which analyze the economic value of R&D or patents: Blundell *et al.* (1995), Toivanen *et al.* (2002), Bloom and Van Reenen (2002), Hall and Oriani (2006), and Greenhalgh and Rogers (2006).

Several of these studies rely on R&D expenditure which is usually considered a measure of innovation input rather than innovation output or 'success' of innovative activities. Moreover, especially in the case of European firms, data on R&D expenditures are often missing because reporting these expenditures is not required by accounting and fiscal regulations across most European countries. The UK is probably the only country where an explicit recommendation of accounting practice was issued in 1989 to foster firms to disclose their R&D expenditures (Toivanen *et al.*, 2002).

Patents as a measure of innovation have their own drawbacks too but, as Griliches (1990: 1661) has remarked, 'in this desert of data, patent statistics loom up as a mirage of wonderful plenitude and objectivity'. Patents have captured the attention of large numbers of studies based on US data but, as mentioned before, there are very few systematic attempts to examine their implications for the market value of the patent holder in the European context.

This paper fills in part this gap in the literature by analyzing an unbalanced sample of firms from five EU countries - France, Germany, Switzerland, Sweden and the UK in the period 1985-2005. With few exceptions, earlier studies focus on single countries. Our work contributes to this literature by exploring the impact of R&D and patents in countries with different institutional settings. Moreover, our analysis is centred on firms from different sectors, including business services and utilities. This allows one to account for potential cross-industry differences in the evaluation of intangible assets.

One motivation for this paper is to gain a deeper understanding of the 'patent paradox', that is, the fact that the number of patent applications to the USPTO and the EPO continues to grow despite the weakness of patents as an instrument for protecting innovation, documented in various surveys of innovators from different industries (Levin et al 1987; Cohen, Nelson and Walsh, 2000; Arundel 2001, 2003).

Another motivation is the dramatic increase in the number of patents in relatively new subject matters, such as semiconductors, software and business methods during the 1990s. This trend raises the question whether the 'value' of patented inventions has declined as a consequence of institutional changes that have lowered the barriers to patents or whether it simply reflects increases research and technological change in these fields. To address this issue we conduct a fine grained examination of the economic value of software patents.

As Hall and Ziedonis (2001) have noted, the rising number of US patents to semiconductor inventions in the 1980s has paralleled a pro-patent shift in the US legal environment. Their analysis shows that large, incumbent semiconductor manufacturers have reacted aggressively to this twist in the IPR regime by widening their patent portfolios. According to Hall and Ziedonis the increase in patent/R&D ratio for these firms is explained by the need to reduce the risk of being held up by other patent owners and to gain stronger contractual power towards competitors. This evidence supports the hypothesis of 'patent portfolio races' or 'strategic patenting', i.e., the race to obtain patents that are not used by the patent holder but serve as a barriers to competitors. However, new firms have entered the semiconductor market during the 1980s. These newcomers, and especially 'technology specialists' (firms specialized in chip design), showed a higher propensity to patent compared with firms entered before. This is probably explained by the need to attract venture capital and protect themselves from larger competitors (Hall and Ziedonis refer to this effect as the 'specialization hypothesis'). The evidence provided by Hall and Ziedonis (2002) then points out the existence of multiple potential effects of the declining patent costs.

Scholars looking at software-related patents have found evidence consistent with the hypothesis of strategic patenting. For example, Bessen and Hunt (2004) have examined software patents granted by the USPTO during the 1990s. A few key decisions taken by the Courts of Appeals for the Federal Circuit (CAFC) in these years led the USPTO to release new guidelines for software patentability in 1996 which allowed patent of any software embodied in physical media. In 1998 an important decision of the US Federal Circuit removed most of the exceptions to the patentability of software ‘as such’, i.e., independently of its links with a physical device. Not surprisingly, the number of software patents granted by the USPTO has increased dramatically during the 1990s. Studies which propose different definitions and estimation criteria agree that the number of USPTO software patents is large and the concentration of patents is also very high (Bessen and Hunt, 2004; Graham and Mowery, 2003; Hall and MacGarvie, 2006). Bessen and Hunt (2004) pointed out that IBM alone accounts for 20% of software patents. Moreover, most software patents are owned by large manufacturing firms in the electronics, telecommunications equipment, and computer industries. This supports the ‘strategic patenting’ hypothesis. Instead, the small share of software patents held by specialized software firms (only 6 per cent according to Bessen and Hunt) appears to reject the ‘specialization hypothesis’. Moreover, Bessen and Hunt have noticed that firms with a larger share of software patents in total patents have reduced their R&D expenditures. They argue that the substitution between R&D expenditures and patents can be explained by strategic patenting behaviour. Firms with large patent portfolios tend to reduce their R&D (relative to patents) because they can now license the technologies covered by other firms’ patents. On the other hand, smaller firms with limited patent portfolios have limited opportunities to appropriate the economic benefits of their R&D activity and this reduces their incentive to invest in R&D. Bessen and Hunt do not consider alternative explanations such as that unrelated changes in technology or management which may result in higher R&D productivity (see, for example, Kortum and Lerner 1998).

We have analyzed EPO patents and found an increasing number of software-related patents during the 1990s.[2] This suggests that the barriers to software patents have fallen in Europe as well, despite the fact that according to the European Patent Convention (EPC) (Art 52) computer programs 'as such' are excluded from the patentable subject-matter. The EPO recognizes the patentability of computer-implemented inventions (CII), that is 'inventions whose implementation involves the use of a computer, computer network or other programmable apparatus, the invention having one or more features which are realized wholly or partly by means of a computer program" (EPO, 2005:3). In 2002 the European Commission released a proposed Directive on the Patentability of CIIs which was rejected by the European Parliament in 2005.

Recently the EC has proposed a new treaty, the 'European Patent Litigation Agreement' (EPLA) which would establish a new European Patent Court which has revamped the debate on the economic implications of patents among practitioners and policy makers through Europe. It is unclear whether this proposal would represent a significant step towards a 'community-wide' patent and how it will affect software patents. However, the proposal testifies to the great concern of the EPO and the EC about patent 'quality' and the effectiveness of the patent examination system.

Our paper contributes to this debate by offering novel empirical evidence about the 'quality' of EPO patents measured by indicators such as the number of forward citations. Moreover, we provide a quantitative assessment of the private returns to patents in a sample of European firms in different sectors. Obviously, finding a significant private value of patents to patent holders does imply that there is any impact on welfare. However, finding that patents are of limited value to their holder would cast serious doubts over their value for

[2] For a detailed analysis of software-related patent applications and the search methodology used to identify this category of patents, see Thoma and Torrisi (2005)

the society. The paper is organized as follows. Section 2 illustrate the method for estimating the market value of R&D and patents, Section 3 illustrates the data and describes the main variables while Section 4 reports the main results. Section 5 discusses the results and closes the paper.

2. Estimating the economic value of intangible assets

There are two streams of the literature that attempt to evaluate the economic returns to innovative activities. First, a series of studies have examined the impact of innovation on total factor productivity or profit growth. Second, other scholars have focused on the private returns to innovation by using a forward looking measure of firm performance which is the valuation of R&D and patent stock relative to physical assets in the stock market (see Hall, 1999 for a survey). The two approaches have both merits and weaknesses.

Total factor productivity (TFP) is simply the ratio of outputs to inputs both expressed in real terms. Taking the natural logs of all variables the TFP can be expressed as follows:

$$log(TFP) = log(S) - \alpha \cdot log(L) - \beta \cdot log(K) \tag{1}$$

This ratio is an appropriate measure of productivity under conditions of constant returns to scale and competition in the markets for inputs and outputs. Several studies have showed the importance of technology, measured by R&D expenditures, for the growth of total factor productivity (e.g., Gold, 1977, Mansfield, 1968, and Griliches, 1979).

Besides the strong assumptions behind the TFP estimations, a major problem with this approach is represented by the fact that the lag between R&D and its impact on productivity or profits is usually long and difficult to predict. Since this gives rise to serious measurement problems when the data are not available in long time series, most empirical works turn their attention to alternative methods. Moreover, using purely accounting measures of firm performance fails to account for the effects of differences in systematic risk, temporary disequilibrium effects, tax laws and accounting conventions.

These limitations are less important with the market value approach which combines market value data with accounting data (Lindenberg and Ross, 1981; Montgomery and Wernerfelt, 1988). The market value approach draws on the idea, derived from the hedonic price models, that firms are bundles of assets (and capabilities) which are difficult to disentangle and to price separately on the market. These assets include plants and equipment, inventories, knowledge assets, customer networks, brand names and reputation. The market value approach draws on the hypothesis that financial markets assign a correct value to the bundle of firms' assets. This approach has been used in several studies to calculate the marginal shadow value of the knowledge assets from the estimation of market value equations (Griliches, 1981; Griliches *et al.* 1991; Hall, 1993 and 1999; Hall *et al.* 2005).

The marginal return to knowledge assets from an intertemporal maximization program with many capital goods is extremely difficult to determine (see Wildasin, 1985). In several econometric studies this difficulty has been tackled by assuming that the market value equation takes a linear form or a Cobb-Douglas one.

The typical linear market value model, relying on the assumption that a firm's assets enter additively, takes the following form

$$V_{it}(A_{it}, K_{it}) = q_t(A_{it}, + \gamma_t K_{it})^{\sigma t} \qquad (2)$$

where A represents the physical assets and K the knowledge assets of firm i at time t. Under constant returns to scale ($\sigma_t=1$) equation (2) in log form can be written as

$$logV_{it} = logq_t + logA_{it}, + log(1+\gamma_t K_{it} /A_{it}) \qquad (3)$$

or

$$logV_{it}/A_{it} = logq_t + log(1+\gamma_t K_{it} /A_{it}) \qquad (4)$$

The left hand side of equation (4) is the log of Tobin's q, defined as the ratio of market value to the replacement cost of the firm, which is typically measured with the replacement value of firm's physical assets. In the right hand side γ_t is the marginal or shadow value of the ratio of knowledge capital to physical assets at a given point in time. It measures the expectations of the investors over the effect of the knowledge capital relative to physical assets on the discounted future profits of the firm. The intercept represents the average Tobin's q for the sample firms while $q_t * \gamma_t$ is the absolute hedonic price of the knowledge capital.

As in Hall *et al.* 2005, equation (4) will be estimated by non-linear least squares. Most earlier research, beginning with Griliches (1981), have approximated the $log(1+\gamma_t K_{it} / A_{it})$ with $\gamma_t K_{it} / A_{it}$ and have estimated the market value equation by ordinary least squares.[3] To ease the comparability of coefficient estimates concerning variables measured in different units we calculated the semi-elasticity of Tobin's q with respect to each of the main regressors

$$\frac{\partial \log Q_{it}}{\partial X_{it}^{j}} = \frac{\gamma_j}{1+\gamma_1(RD_{it}/A_{it})+\gamma_2(P_{it}/RD_{it})+\gamma_3(CIT_{it}/P_{it})} \qquad (5)$$

where X^j_{it} is the regressor of interest - R&D stock/physical assets, patent stock/R&D stock (total or software patents) and citation stock/patent stock. We calculated the semi-elasticities given by equation (5) and their standard errors using the "delta" method for each observation in the dataset and then averaged them. The tables show the average semi-elasticity and its average standard error.

We should notice that shadow prices are equilibrium prices resulting from the interaction between the firm's demand and the market supply of capital for a specific asset at a given point in time.[4] While shadow prices can vary across countries and over time, the

[3] We have also used OLS for comparison but the results are not reported here due to lack of space.

[4] This implies that no structural interpretation should be attached to estimates of the market value equation.

values obtained by estimation of the market value equation measure the current average marginal shadow values of an additional euro spent in R&D or an additional patent filed.[5]

The market value approach rests on restrictive hypotheses concerning the efficiency of the capital markets and therefore it can be used only for private firms quoted in well-functioning stock markets. In fact, financial markets are imperfect and there are persistent institutional differences across countries which result in different evaluation of intangible assets. Imperfections in the product markets in general also tend to persist over time and, therefore, they can be ignored when the analysis focuses on variations of the market value over time within sector. Moreover, country dummies may account for some institutional differences across countries.

Not surprisingly, most empirical studies which follow this approach rely on data from the US and the UK, where the stock markets are more efficient compared with other countries. For related reasons, studies based on US data also benefit from the availability of large sets of firm-level panel data. These studies find that R&D stocks are significantly valued by financial markets in addition to physical assets. The empirical evidence for the US also shows that patent counts have an additional, albeit weaker, effect on market value after controlling for R&D. Finally, Hall *et al.* 2005 find that citation-weighted patents are more informative than mere patent counts about the market value of innovation.

A series of studies based on European datasets have used different indicators of innovation (R&D, patents and patent citations) confirming that, by and large, innovative assets impact significantly upon the firm market value (see Table 1 for a list of such studies).

[5] For a more detailed discussion of various problems concerning the estimation of the market value equation, see Hall (2000).

Table 1. Empirical Studies of the Market Value of Innovation in Europe

Paper	R&D	Innovation output	Patent citations	Sample size	Geographical coverage	Time period
Blundell *et al.* (1999)	NO	USPTO patents, SPRU innovation counts	NO	340	UK	1972-1982
Bloom and Van Reenen(2002)	NO	USPTO patents	5-year cite stock	404	UK	1968-1996
Toivanen *et al.* (2002)	YES	NO	NO	1519	UK	1988-1995
Hall and Oriani (2006)	YES	NO	NO	2156	US, UK, FR, IT, DE	1989-1998
Greenhalgh and Rogers (2006)	YES	UK and EPO patents	NO	3227	UK	1989-2002

3. Data

3.1. Sample

To construct our sample we started from 3,090 publicly traded firms whose headquarters are located in France, Germany, Great Britain, Switzerland and Sweden over the period 1980-2005. This selection of countries accounts for potential cross-country differences in financial institutions and accounting regulations. Only 731 firms reported data on R&D expenditures for at least one sample year. For these firms we collected data on patents and found that 387 have been granted at least one patent and 122 at least one software patent by the EPO in the period 1985-2005.

Data on corporate structure (date of incorporation, ownership structure, ultimate parent company, subsidiaries) and balance sheet were obtained from the Bureau van Dijk's Amadeus database. Data on market capitalization were obtained from Thomson Financial's Datastream. R&D data were obtained from Amadeus and the UK Department of Industry's R&D Scoreboard. More precisely, we extracted from Amadeus all quoted companies reporting positive R&D expenditures for at least one year between 1980 and 2005. From the

R&D Scoreboard we retrieved R&D expenditures for 22 publicly-traded firms whose R&D expenditures were not available from Amadeus.

Firms' patent counts in all technological classes were obtained by matching the name of the assignee from the CESPRI-Bocconi University patent database with the company name in Amadeus. Patent citations and the number of IPC classes were extracted from the PATSTAT database, available under license from the EPO-OECD Taskforce on Patent Statistics (PATSTAT 2006).

For companies with more than one subsidiary, the patents of the ultimate parent company have been consolidated on the basis of the 2005 ownership structure reported in Amadeus. Further information on corporate structure was collected from Hoovers, Who Owns Whom, and company websites. Holding companies have been reclassified manually according to the main line of business or their most important subsidiaries using additional information from Amadeus, Hoovers, and company websites. In future research we will check for changes in corporate structure of the sample firms by using information on annual ownership structure provided by Amadeus and Who Owns Whom before 2005.

As Table 2 shows, the sample of R&D reporting firms is clearly biased in favor of large firms (over 500 employees), especially in France and Switzerland. This sample selection bias is due to the availability of data on market capitalization. Medium sized firms are better represented in the United Kingdom, Sweden and Germany than in France and Switzerland. A large share of the firms for which employment data are not available are most probably small. Tables A.1 and A.2 in Appendix A report the distribution of the firms in the sample by capitalization and the main stock markets involved.

Table 2. Country-size distribution of R&D-reporting firms

Size range	France		Germany		Sweden		Switzerland		United Kingdom		All	
(employees)	Firms	%	Firms	%	Firms	%	Firms	%	Firms	%	Firms	%
50-100	3	5.1	5	3.7	7	8.6	2	3.0	54	13.8	71	9.7
100-500	10	16.9	43	32.1	19	23.5	8	12.1	115	29.4	195	26.7
>500	41	69.5	66	49.3	38	46.9	53	80.3	141	36.1	339	46.4
Not available	5	8.5	20	14.9	17	21.0	3	4.5	81	20.7	126	17.2
All sizes	**59**	**100.0**	**134**	**100.0**	**81**	**100.0**	**66**	**100.0**	**391**	**100.0**	**731**	**100.0**

Almost half the firms in this sample have a market capitalization less than 100 million dollars and the majority of firms with very high capitalization (above 5 billion dollars) have been established before 1970. Moreover, around 25 per cent of firms with a capitalization between 1 and 5 billion dollars have been incorporated after 1990. This is in part the result of restructuring, liberalization and privatization of formerly state-owned corporations in many European continental countries during the 1990. Another reason is the entry of software and 'internet economy' companies such SAP, Business Objects, Infineon Technologies and O2.

R&D-reporting firms cover a large number of sectors (see Table A.3 in the Appendix). The distribution of patents and R&D expenditures across industries is reported in Table A.4. The most important sectors in terms of R&D expenditures are motor vehicles, pharmaceuticals, and electronic instruments & telecommunications equipment. Along with chemicals and soap & toiletries, these are also the most important sectors in terms of total patents. However, a single sector, electronic instruments & telecommunications equipment, accounts for over half the software patents.

3.2. Variables

Our dependent variable is Tobin's q for the firm, that is, the ratio of the firm's market value to tangible assets. Firm's market value is defined as the sum of market capitalization (price multiplied by the number of outstanding shares at the end of the year) and non current liabilities less a correction for net current liabilities plus inventories. Tangible assets are the net costs of tangible fixed property and inventories used in the production of revenue, and are obtained as the sum of gross fixed assets plus inventory stocks less depreciation, depletion, and amortization (accumulated), investment grants and other deductions.[6]

The R&D expenditure history of each firm was used to compute R&D stock. R&D spending includes amortization of software costs, company-sponsored research and development, and software expenses. It is important to note that availability of data on R&D expenditures is potential source of sample selection bias. European firms are not required or recommended to disclose information on their R&D expenditures. Announcing R&D is then an endogenous variable since the decision whether or not to disclose this information rests upon the discretion of the firm. We treat this issue in Section 4 of the paper.

R&D stocks were obtained using a declining balance formula and the past history of R&D spending. $KRD_t = R\&D_t + (1-\delta)KRD_{t-1}$, where δ is the depreciation rate. We chose the usual 15 per cent depreciation rate. Our starting R&D stock was calculated for each firm at the first available R&D observation year as $KRD_o = RD_o/(\delta+g)$. This assumes that real R&D has been growing at a constant annual growth prior to the sample; we used a growth rate g of 8 per cent. Patent stocks were obtained using the same methods, except that the initial available patent counts were not discounted to obtain an initial capital stock because EPO patents started at the beginning of our sample.[7]

Our controls include firms' annual sales, which account for scale effects in the market value equation, industry dummies, country dummies and year dummies. Firms' R&D and sales have been depreciated by the annual GDP deflator extracted from the AMECO-

---

[6] All values expressed in domestic currencies have been converted into euros by using annual average exchange rates reported by EUROSTAT.

[7] Of course, prior to the creation of the EPO, these firms were acquiring patents from their individual patent offices, but it would require resources beyond our capabilities to assemble these data and the added value would be minor, given our focus on the period after 1984.

EUROSTAT web directory. Following Hall and Oriani (2006), we control for differences in the corporate structure. To this purpose, we generated three dummies which take value 1 when the main shareholder holds a share higher than 35 per cent, 40 per cent and 50 per cent respectively. This information is reported in the Amadeus dataset.

3.3. Software patents

One of the goals of the research reported here was to get a picture of the use and valuation of European software patents in European firms. Moreover, as mentioned before, there is a growing attention to software patents amongst business practitioners, scholars and policy-makers. Critics claim that software patents have an average poor quality and are applied for ‘strategic’ reasons rather than for protecting real inventions, whereas advocates maintain that software inventions are technological inventions like any other and show be entitled to patentability.

A series of recent papers using U.S. data have examined software patents empirically in that country (Bessen and Hunt 2004; Graham and Mowery 2003; Hall and MacGarvie 2006), but we are not aware of similar studies that draw on EPO data. The studies mentioned before are interesting for two reasons. First, they propose different workable definitions of ‘software patents’ that we can use to construct a sample of EPO software patents. Second, they provide interesting results on the introduction of software patenting in the U.S. that can be used as a reference point for our study.

Even in the U.S., it is difficult to find a simple definition of a software-related patent that can be used for statistical purposes and in Europe things are even more difficult because the international patent classification system does not actually recognize their existence. Therefore, the definition of software-related patents used in this study draws on earlier studies on USPTO data. The three main alternatives are those used by Graham and Mowery (2003), Bessen and Hunt (2004), and Hall and MacGarvie (2006).

Graham and Mowery identify as software patents those that fall in particular International Patent Classification (IPC) class/subclass/groups. Broadly defined, the class/subclasses are “Electric Digital Data Processing” (G06F), “Recognition of Data; Presentation of Data; Record Carriers; Handling Record Carriers” (G06K), and “Electric Communication Technique” (H04L).[8] Graham and Mowery selected these classes after examining the patents of the six largest producers of software in the U.S. (based on 1995 revenues) between 1984 and 1995. Patents in these classes account for 57% of the patents assigned to the hundred largest firms in the software industry.[9]

An alternative definition is that adopted by Bessen and Hunt who define software patents as those that include the words “software” or “computer” & “program.” in the patent document description. Patents that meet these criteria and also contain the words “semiconductor”, “chip”, “circuit”, “circuitry” or “bus” in the title are excluded under the assumption that they refer to the device used to execute the computer program rather than the program itself.

Hall and MacGarvie (2004) suggest a third algorithm to define software patents that identifies all the U.S. patent class-subclass combinations in which fifteen “pure” software firms patent, yielding 2,886 unique class-subclass combinations. Patents falling in the classes and subclasses combinations obtained from this search method are defined as software patents. The definition preferred by Hall and MacGarvie combines this definition with that of Graham and Mowery and then takes the intersection of the result with the Bessen-Hunt sample.

We followed a combination of the search methods above to identify software patents in the EPO dataset. First, we searched the title, abstract, claims and description of patents in

[8] The groups included are G06F: 3,5,7,9,11,12,13,15; G06K: 9,15; H04L: 9.

[9] Graham and Mowery (2003), p. 232. The firms are Microsoft, Adobe, Novell, Autodesk, Intuit, and Symantec.

the EPO dataset by relying on the same keywords used by Bessen and Hunt in their 2002 study of US software patents: ((software) OR (computer AND program)) AND NOT (chip OR semiconductor OR bus OR circuit OR circuitry <in> TI) AND NOT (antigen OR antigenic OR chromatography). This procedure yielded 11,969 patents (in 7,117 different IPC classes-subclasses) (the *keyword method* hereafter). Second, we analyzed the IPC (International Patent Classification) classes of the patent portfolios of the world's 15 largest specialized software firms (the IPC method hereafter). We expanded the set of firms used in earlier studies to obtain a representative sample of specialized software firms including European companies.[10] Our sample firms account for over 30% of the world software market ($227bn according to European Information Technology Observatory estimates). They have been granted 373 patents in 3,518 different technological classes-subclasses (117 if one considers only the main IPC codes in each patent).

We have combined the keyword and IPC method to define software patents (we took the union of the patents obtained with the two methods).[11] To identify software patents we relied on the Delphion dataset (www.delphion.com), which gives access to the full-text of patent document, including the application date, the number of countries for which patent protection is asked for (family size), the technological classes and the address of the assignee.

[10] The top European software patenters over 1978-2004 are Microsoft, Oracle, Peoplesoft, Veritas, Symantec, Adobe Systems, Novell, Autodesk, Intuit, Siebel Systems, Computare, BMC Software, Computer Associates, Electronic arts (Japan), and SAP (Germany), whereas the top U.S. software patenters during the 1980-2000 period are Microsoft, Oracle, Peoplesoft, Veritas, Symantec, Adobe Systems, Novell, Autodesk, Macromedia, Borland, Wall Data, Phoenix, Informix, Starfish, and RSA Security. Only half the firms are common between the two lists, and only two firms are not U.S.-based.

[11] By relying on the union between the two methods we reduce the Type I-error (excluding a patent that we should have included among software patents) but may incur in a high Type-II error (classify as software patent a patent that is not related to software). A study based on software expert examination of earlier studies of USPTO patents classified according to the keyword method has found a low Type-I error but a high Type-II error using a similar methodology (Hall and MacGarvie 2006; Layne-Farrar 2005).

3.4. Descriptive statistics

Table 3 shows some descriptive statistics for the final sample of 572 firms, an unbalanced panel with 3,555 observations (from 1 to 20 years per firm). In this table the statistics for all of the patent variables are based only on the non-zero values of these variables. The variables considered are patents excluding software patents and software patents, each as raw counts, weighted by citations received, and then weighted by a quality index constructed from citations made, citations received, and the number of classes. For each of these six variables, we have the annual flow, a stock computed as described earlier, and various ratios.

Table 3. Descriptive statistics

3555 observations, 572 firms, 1985-2005								
Variable	**N**	**Mean**	**s.d.**	**Median**	**1Q**	**3Q**	**Min**	**Max**
Employment (1000s)	3471	19.3	49.7	1.7	0.4	11.69	0.01	477.1
Annual sales*	3547	4273	12610	282	56	1968	0.02	190,000
Tobin's q	3555	2.93	3.28	1.78	1.17	3.19	0.11	24.91
R&D expenditures*	3555	163.8	590.0	8.1	1.8	44.2	0.00	6,782
R&D stock*	3555	843.2	3095.6	37.9	9.2	213.5	0.05	35,160
R&D stock/assets	3555	0.57	0.77	0.29	0.12	0.68	0.00	4.98
Annual patents	2044	12.9	59.4	0	0	2	0.00	761
Patent stock	2044	90.3	369.1	3.9	0.9	26.9	0.02	4,099
Pat stock/R&D stock*	2044	0.20	0.52	0.05	0.02	0.16	0.00	11.59
Annual software patents	789	1.5	7.0	0	0	0	0.00	77
Software patent stock	789	8.6	35.0	1	0.6	2.5	0.05	340.7
Software pat stock/R&D stock*	789	0.03	0.17	0	0	0.01	0.00	3.10
Annual citation-weighted patents	1503	34.6	162.7	0.00	0.00	3.2	0.00	2,360
Citation stock	1503	326.7	1106.9	9.7	2.2	135.7	0.02	10,813
Citation stock/Patent stock	1503	2.66	3.14	1.87	1.01	3.31	0.02	22.80
Annual citation-weighted software patents	497	3.37	15.52	0.00	0.00	0.00	0.00	151.01
Software patent citation stock	497	25.3	72.7	3.5	1.5	9.3	0.07	484.4
Soft pat cite stock/Soft pat stock	497	3.24	3.32	2.49	1.08	3.95	0.06	18.94
Annual composite ‘quality’ index for all patents**	644	2.10	10.52	0.00	0	0.80	-51.46	107.97
Composite ‘quality’ index wtd patent stock**	644	18.5	47.2	1.9	0.5	16.1	0	398.2
Composite ‘quality’ Index stock/Pat stock**	644	0.42	0.64	0.18	0.08	0.53	0	3.19
Annual composite ‘quality’ index (software patents)**	218	0.22	1.88	0.00	0	0	-5.23	21.78
Composite ‘quality’ index stock (software patents)**	218	1.65	3.09	0.73	0.27	1.48	0.01	27.16
Composite ‘quality’ Index stock/Pat stock (software patents)**	218	0.61	0.61	0.34	0.12	0.83	0.01	2.14

* millions of current euros

** for 1980-2000 only

4. Results

4.1. Estimation of the basic model without citations

The basic model that includes R&D stocks, total patent stocks and software patent stocks was estimated using nonlinear least squares (NLLS) on equation (4).[12] We also computed the elasticity of Tobin's q with respect to the main regressors and averaged them across all observations. The results are shown in Table 4 and the main findings can be summarized as follows.

First, the ratio between R&D stock and physical assets is positively and significantly related to Tobin's *q* across different specifications of the market value equation. The magnitude of the coefficient (slightly less than unity) is consistent with most of those reported in earlier works on single or multiple countries (e.g., Hall 2000; Blundell *et al.* 2002; Toivanen *et al.* 2002; Hall and Oriani 2005; Greenhalgh and Rogers 2006). Second, in all specifications a firm's patent stocks are significantly related to value, above and beyond the R&D stock that generated them. The magnitude of the coefficient is substantially higher than the coefficient obtained by Hall *et al.* 2005 using the same methodology for U.S. firms and U.S. patent data during the 1980s: approximately 0.3 as compared with 0.03 for the earlier period and data. However, it is closer to the estimate obtained by Hall and MacGarvie 2006 for a sample of US information and communication technology (ICT) firms during the late 1990s, which was 0.15. Note that the estimates here are probably the first set of estimates using patents for firms from continental European countries and they do seem to suggest that EPO patents have somewhat higher value for the firms than U.S. patents. The semi-elasticities computed at the variable means that are reported in Table 4 indicate that a one

[12] OLS estimates of the log approximation to equation (4) produced similar results and are therefore not shown.

standard deviation increase in the ratio of R&D stock to physical assets yields an increase in market value of approximately 35 per cent, whereas a one standard deviation increase in the number of patents per million euros of R&D stock yields a 8.8 per cent increase in market value.[13]

The software patent stock, which is only two per cent of the total patent stock on average, has a significant negative discount in the market value, which implies that the net effect of having software patents is near zero (the difference of the semi elasticities is about 0.03). Note that software patents are highly concentrated in a few sectors and firms: Table A.4 reports the distribution of software patents by sectors. The most important sector in terms of software patents is electronic instruments & telecommunications equipment, which accounts for 62 per cent of total software patents in our sample. Other important software patent holders are firms in the telecommunication services sector, computers, motor vehicles and pharmaceuticals. IBM accounts for about 10 per cent of total EPO software patents granted to business enterprises, followed by Siemens and Canon (about 4 per cent each). Other large electronics firms are also relatively large software owners – e.g., Philips (3.4 per cent) and Sony (2.5 per cent). The largest software firm among the top owners of EPO software patents is Microsoft with a one per cent share.

Patent concentration in our dataset is even higher since all non-European firms are excluded. As a consequence, Siemens alone accounts for 60 per cent of total software patents in the sample. Moreover, the largest 15 software patent holders account for over 90 per cent of total software patents and the first specialized software firm on the list is SAP of Germany, with 0.4% of the patents. The high concentration of software patents makes the interpretation of the coefficient in the market value equation quite problematic. As a robustness check we

[13] The numbers reported in the bottom panel of Tables 4 and 5 are average semi-elasticities across all firm-year observations and their average standard errors.

estimated our equations by excluding Siemens but the results reported in Table 4 remain unchanged. The fact that software patents have little or no impact on the firm market value is therefore common to other firms in our sample.

Table 4. Market valuation equation estimates including R&D and patent stocks

Dependent variable= log of Tobin's q
(3555 observations, 572 firms, 5 countries, 1985-2005)

Variable	(1)			(2)			(3)			(4)		
R&D stock/assets	0.99	(0.07)	***	0.81	(0.07)	***	0.88	(0.09)	***	0.81	(0.09)	***
Pat stock/R&D stock							0.32	(0.08)	***	0.31	(0.08)	***
D (no patents)							-0.005	(0.030)		0.006	(0.029)	
SW pat stock/R&D stock										-0.25	(0.11)	**
D (no SW patents)										-0.05	(0.03)	
Log (sales)				-0.024	(0.005)	***	-0.019	(0.006)	***	-0.021	(0.006)	***
D (sales missing)				0.59	(0.59)		0.74	(0.65)		0.69	(0.61)	
Adjusted R-squared	0.234			0.237			0.245			0.245		
Standard error	0.700			0.699			0.695			0.695		
Mean semi-elasticities (mean standard errors)												
R&D stock/assets	0.525	(0.047)		0.429	(0.046)		0.467	(0.056)		0.433	(0.056)	
Pat stock/R&D stock							0.170	(0.042)		0.167	(0.043)	
SW pat stock/R&D stock										-0.135	(0.057)	

All equations include country dummies, year dummies, and industry dummies
Nonlinear least squares estimates with standard errors robust to heteroskedasticity

4.2. Sample selection bias

As mentioned before, the disclosure of R&D expenditures is an endogenous variable and this gives rise to potential sample selection bias. To see whether sample selection biases our results, we first calculated the share of total R&D in the population of manufacturing and utility firms accounted for by our sample. Country-level R&D expenditures were taken from the OECD STAN dataset. The ratio of total R&D in our sample to the country-level industrial R&D was about 0.46 in France, 0.82 in Sweden, 1.56 in Switzerland, 0.66 in the UK and 0.35

in Germany.[14] Apparently, the problem of sample selection is potentially relevant for German and French firms while it is less important for other firms in our sample. Overall, the high coverage of national R&D expenditures demonstrates that in Europe, as in the US, most of the business R&D activity is conducted by large, publicly traded firms. Moreover, our sample accounts for around 15.9% of overall patenting activity and 6.7% of software patenting activity at the EPO. These shares are quite large given that our sample is centered on only five European countries and firms from the United States and Japan are excluded.

To check for sample selection bias we estimated a sample selection model using the Heckman two step method. For this purpose we collected accounting data on a matching sample of 1,736 publicly-listed firms from the same five countries which have reported no R&D data over the period 1980-2005.[15] Table A.5 in the Appendix reports the differences between the two samples with respect to the key variables used in our analysis. The non-R&D doing firms are smaller, less labor-intensive, have higher leverage, and lower Tobin's q.

In the selection equation whether or not the firm discloses R&D spending is regressed on the following set of variables: leverage (the ratio of current+non-current debt to tangible fixed assets), capital intensity (the ratio of tangible fixed assets to sales), and labor intensity (the ratio of labor cost to sales), as well as the share of the firm held by the main shareholder. These regressors account for observable firm characteristics that can affect its decision whether or not to reveal R&D expenditures. To account for 'environmental' factors we included industry and year dummies in the equation. The inverse Mills' ratio obtained from the first stage estimation was then entered in the market value equation. Preliminary results

[14] The fact that the share for Swiss firms is above unity is explained by the R&D activity of their foreign subsidiaries in countries like the United States, Germany and France.

[15] The sample includes all publicly listed firms in the sample countries which whose accounting data are available in Amadeus company directory.

show that there is little evidence of sample selection except for Swedish firms.[16] This result is consistent with that of Hall and Oriani (2005) for firms in France, Germany, and Italy.

4.3. Differences in patent quality

Research on the economic importance of patented inventions have demonstrated that the distribution of patent value is very skewed (e.g., Harhoff *et al.* 1999). The large majority of patents have an extremely limited commercial value and only few represent an important source of revenues to the assignee. A variety of indicators have been adopted to correct for variation in the importance of patents, the most popular of which is the number of forward citations.

Citations, i.e., citations of 'prior art' that is relevant to a patent, serve an important legal function, since they delimit the scope of the property rights awarded to the patent. Thus, if patent B cites patent A, it implies that patent A represents a piece of previously existing knowledge upon which patent B builds, and over which B cannot have a claim. Citations to other patents then can be considered as evidence of spillovers or knowledge flows between patented inventions. However, the usefulness of citations as a proxy for knowledge spillovers is limited by the fact that citations are not always added by the inventor (Hall *et al.* 2005). In the US, the applicant is required to disclose her knowledge of the prior art, although in fact, references to prior art are often found by the inventor's patent attorneys, rather than the inventor, and the decisions regarding which patents to cite ultimately rests with the patent examiner, who is supposed to be an expert in the area and hence to be able to find prior art that the applicant misses or conceals.

In the case of EPO patents, inventors are not required to cite prior art and therefore references to earlier patents are usually added by patent examiners. This suggests that patent

[16] The results of these estimations are available upon request.

citations in EPO patents are even less useful as a measure of spillovers. However, compared to the USPTO, citations contained in EPO patents tend to be more consistent and objective because they are assigned by the same team of patent examiners.

For our purposes here, the key question is whether backward citations are a good measure of the quality of the citing patent. Some scholars have suggested that large numbers of citations to others reveal that a particular invention is likely to be more derivative in nature and, therefore, of limited importance (Lanjouw and Schankerman 2004). However, a large number of backward citations may also indicate a novel combination of existing ideas. This is probably the reason why Harhoff *et al.* (1999) have found that backward citations are positively correlated with patent value.

Forward citations received by a patent indicate that the information in an invention has served as a base for a future invention. Our analysis relies on counts of forward citations over a five year period between the publication date of the cited patent and the application date of the citing patent. Due to the short time the EPO has been in existence, a wider time window would dramatically reduce the number of observations.

Other potential indicators of patent value are the number of claims (which delimit the scope of the invention), family size (the number of jurisdictions or countries the patent has been applied for) and the number of different technological classes assigned by patent examiners to a given patent. We use the number of technological classes because they have been shown to be an indicator of technological 'quality' like the number of citations (Lerner 1994). To guarantee a reasonable level of precision , we use eight-digit IPC classification codes (IPC) reported in the patent document. The number of IPC classes can be viewed as a measure of technological scope or generality of the patent even though, as noted by Guellec and Pottelsberghe de la Potterie (2000), it may be also a measure of ambiguity reflecting the difficulty of the examiner in locating the invention in the technological space.

To adjust for variations in the technological and economic value of patents in our estimations we use, alternatively, forward citations and a composite index of patent 'quality' derived from a model developed by Lanjouw and Schankerman (2004). This index is estimated by a common factor model that explains the variance of the three indicators discussed before. Our common factor is a linear combination of backward citations, forward citations, and number of IPCs. The common factor explains as much as possible the total variance of each indicator while minimizing its idiosyncratic component. The methodology is briefly illustrated in Appendix B. The three indicators are all strongly correlated to each other at the 1% level of significance. It is worth noting that for the calculation of this index we rely on patents (and their citations) until 2001 because patents applied for afterwards have a citation lag window shorter than five years.

Patent citations suffer from several potential sources of biases, the most obvious of which is truncation. The number of citations to any patent is truncated in time because only citations received until the end of the dataset are observed. The observed number of citations to any given patent may also be affected by differences across patent cohorts, technological fields and patent offices. The observed citations then have to be adjusted or normalized for this multiplicity of effects. To this purpose we have adopted the approach developed by Caballero and Jaffe (1993) and Hall *et al.* (2005) – hereafter referred to as the HJT method- which is based on the estimation of a semi-structural model where the citation frequency is explained by cited-year effects, citing-year effects, technological field effects and citation lag effects. The estimated parameters of this model can be used to correct observed citation rates. Appendix C reports a brief description of the HJT method and the cumulative lag distribution by technology field.[17] These expected lag distribution provide the proportion of the lifetime

[17] Bacchiocchi and Montobbio (2004) have also used the HJT method and found significant differences in citation distribution lags between USPTO and EPO patents which reflect different institutional frameworks.

citations that are predicted to occur in the time window observed. Actual citations are divided by predicted citations to correct for truncation.[18]

Table 5 reports NLLS estimations with forward citations and the composite index of patent quality respectively. The first three columns report the results of the base specification with R&D and patent stocks only (corresponding to models 2, 3, and 4 of Table 4) and the last four columns the results when various quality measures for patents are added to the equation. Although based only on data through 2000, the baseline specifications (models 2, 3, and 4) are very similar to those in Table 4, with a slightly higher R&D stock coefficient and higher explanatory power.

Models 5 and 6 add average citations per patent and average citations per software patent to the base specification in models 3 and 4. Both variables are completely insignificant, in contrast to the results in Hall *et al.* 2005 and Hall and MacGarvie 2006, where citations entered positively. That is, EPO patents held by European firms are more closely associated with market value than USPTO patents held by US firms, but the opposite is true of the average rate at which they are cited. Recall that European patent citations are fewer in number and largely added by the examiner, which may help to explain at least part of this finding. But the fact remains that it seems as though the EPO patents are more closely associated with value and therefore have less need of citation-weighting.

In contrast to the result for patent citations, the composite index of patent 'quality' discussed before is significantly associated with the market value of the firm (models 7 and 8). This suggests that, beyond and above the mere counts of patents, patent stocks characterized by a consistent set of technical characteristics (e.g., many backward and

[18] Note that citations used for the estimation of the composite 'quality' index were not corrected for truncation and therefore we rely on observations until 2001 which represents a fairly wide time window. Instead, citation counts used to calculate citation stocks to patent stocks entering the market value equation regression include observations up to 2003. The correction for truncation allows to approach the end of the sample. However, the closer is the cited patent application year to the end of the sample the less reliable tend to be the number of corrected citations. This is why cited patents applied for after 2003 we dropped by the sample.

forward citations, and a wide technology scope) are valued positively by the market. In the presence of patent stocks, the marginal effect of the composite quality index is somewhat less than that of these stocks. As Table 5 shows, a one standard deviation increase in the average quality per patent yields a 5 per cent increase in the value of the firm. In contrast, a one standard deviation increase in the ratio of patent stock to R&D stock yields an 8 per cent increase in value. The market value premium for the average software patent quality index is negative but insignificantly, implying that their quality is evaluated roughly in the same way as other patents. The significant effect of the composite index of 'quality' is in line with the results obtained by Lanjouw and Schankerman (2004) and shows that some patents (those of high technical 'quality') are an important source of economic value.

Various robustness checks of the above results have been done using regressions that excluded extreme values of R&D stocks, patent stocks, the composite 'quality' index and software citation stocks. The qualitative results are very similar. However, these estimations do not account for bias due to unobserved firm-specific heterogeneity. We defer this to future research using panel data estimation.

Table 5 Market valuation equation estimates with quality-adjusted patent stocks

Dependent variable: Log Q
1779 observations, 368 firms, 5 countries, 1985-2000

Variable	(2)			(3)			(4)			(5)			(6)			(7)			(8)		
R&D stock/assets	0.91	(0.10)	***	1.02	(0.14)	***	0.98	(0.15)	***	1.05	(0.14)	***	0.99	(0.15)	***	1.00	(0.13)	***	0.94	(0.14)	***
Pat stock/R&D stock				0.30	(0.09)	***	0.32	(0.10)	***	0.31	(0.09)	***	0.33	(0.10)	***	0.29	(0.09)	***	0.31	(0.10)	***
D (no patents)				0.020	(0.038)		0.027	(0.038)		0.057	(0.046)		0.064	(0.044)		0.004	(0.037)		0.011	(0.036)	
SW pat stock/R&D stock							-0.28	(0.11)	***				-0.29	(0.11)	***				-0.29	(0.11)	***
D (no sw patents)							-0.026	(0.006)					-0.052	(0.047)					-0.030	(0.040)	
Cit stock/Pat stock										0.015	(0.010)		0.015	(0.010)							
SW cit stock/ SW pat stock													-0.009	(0.007)							
Index stock/Pat stock																0.154	(0.045)	***	0.155	(0.045)	***
SW index stock/ SW pat stock																			-0.054	(0.034)	
log (sales)	-0.044	(0.006)	***	-0.040	(0.006)	***	-0.040	(0.006)	***	-0.041	(0.007)	***	-0.041	(0.006)	***	-0.040	(0.006)	***	-0.041	(0.006)	***
D (sales missing)	2.37	(1.58)		2.71	(1.77)		2.63	(1.73)		2.78	(1.79)		2.63	(1.72)		2.63	(1.71)		2.54	(1.67)	
Adjusted r-squared	0.291			0.299			0.299			0.299			0.299			0.302			0.302		
Standard error	0.691			0.688			0.688			0.687			0.687			0.686			0.686		

Mean semi-elasticities (mean standard errors)

Variable	(2)		(3)		(4)		(5)		(6)		(7)		(8)	
R&D stock/assets	0.453	(0.064)	0.509	(0.082)	0.488	(0.085)	0.532	(0.090)	0.500	(0.091)	0.497	(0.079)	0.471	(0.081)
Pat stock/R&D stock			0.148	(0.047)	0.161	(0.053)	0.158	(0.051)	0.168	(0.056)	0.144	(0.047)	0.156	(0.052)
SW pat stock/R&D stock					-0.141	(0.056)			-0.148	(0.058)			-0.144	(0.055)
Cit stock/Pat stock							0.008	(0.006)	0.009	(0.006)				
SW cit stock/ SW pat stock									-0.004	(0.004)				
Index stock/Pat stock											0.077	(0.023)	0.078	(0.023)
SW index stock/ SW pat stock													-0.027	(0.017)

All equations include country dummies, year dummies, and dummies for each of the 5 ICT sectors.
The method of estimation is nonlinear least squares on equation (4) with standard errors robust to heteroskedasticity.

5. Discussion and conclusions

This paper reports novel findings on the economic value of patents in a sample of European firms. The main novelty of the paper consists in the use of EPO patents and quality-adjusted patents in the market value equation. In addition, we explored the question of whether software-related patents in Europe are valued differently from other patents. This exercise was motivated by the growing number of software patents in the EPO, the debate over the patentability of Computer Implemented Inventions and the supposedly poor quality of 'software-related' patents due to their strategic nature.

As far as total patents are concerned, our results demonstrate that most EPO patents held by EPO firms are valued somewhat more than USPTO patents held by US firms, but that the same is not true of software patents. Our analysis shows that software patents have no impact on the firm market value and that their citations are valued no more than those to other patents. Why are these patents valued so poorly by the capital market, despite the fact that their citation intensity and composite 'quality' index are above the average of total patents? It is possible that the market anticipates that software patents in particular are mostly used for strategic reasons rather than signalling the outcome of real inventive activity. The concentration of these patents among hardware firms suggests this hypothesis. Sample firms like Siemens, Alcatel or Thomson may decide to patent their software to prevent litigation and in reaction to the large number of EPO software patents held by large, established non-European competitors like IBM, Canon and Sony. The limited value of software patents may also indicate that the financial market accounts for their weak enforceability due to the legal ambiguity about software and CIIs patentability.

In this setting, the insignificant share of software firms in software patents suggests that most software firms or newly formed firms are not using patents to protect their inventions. This is also one explanation for the difference between our results and those of Hall and MacGarvie (2006) who find that citations to software patents are valued positively by the market in the case of software firms while they are not for hardware firms.

This is a preliminary investigation of the dataset on EPO patents based only on European firms from a limited set of countries. In future research we will try to correct for some limitations of the dataset. First, we want to extend the analysis to other countries and firms, including non-European firms and accounting for the priority date of the patent (i.e., the date of the first application. Our analysis so far is based on the date of application to the European Patent Office. This leads to left censoring of the priority date. Second, we aim to examine citation lags by including citations in non-EPO patents. As mentioned before, in the current version of the paper we assumed that the citation lag distribution does not vary between EPO and non-EPO citing patents. Third, we will control for differences between citations to other patents and self-citations. Although we have included self-citations, we do not expect significant changes in our results. Previous work on US data by Hall *et al.* (2005) and Hall and MacGarvie (2006) have found that removing self-citations yields real but limited changes in the impact of citation-adjusted patents on the firm's market value.

Finally, we will control for changes in corporate structure. The results presented in this paper rely on the corporate structure of the firms as of 2005, which was used to match the name of patent assignees in the EPO database with that of companies in Amadeus. Therefore in earlier years our patent variables may include more or fewer patents than are actually owned by the firm, which introduces an unknown source of bias. We recognize that this is a potential source of bias because expectations about future firms' performance (our dependent variable) may be correlated with future acquisitions of patents, implying that the patent variable proxies for growth expectations in some cases.

Bibliography

Arundel, A. (2001), "The Relative Effectiveness of Patents and Secrecy for Appropriation." *Research Policy* 30: 611-624.

Arundel, A. (2003), *Patents in the Knowledge-Based Economy*, Report of the KNOW Survey, MERIT, University of Maastricht.

Bacchiocchi, E. and F. Montobbio (2004), "EPO vs. USPTO Citations Lags." in *CESPRI Working Papers*.

Bessen, J and Hunt, R. M. (2004), "An Empirical Look at Software Patents," Boston University, Working Paper: http://www.researchoninnovation.org/swpat.pdf

Bloom, N., and J. Van Reenen (2002), "Patents, real options and firm performance." *Economic Journal* 112: C97-C116.

Blundell, R., R. Griffith, and J. Van Reenen (1999), "Market share, market value and innovation in a panel of British manufacturing firms." *Review Of Economic Studies* 66: 529-554.

Blundell, R., R. Griffith, and J. Van Reenen (1995), "Market Share, Market Value, and Innovation in a Panel of British Manufacturing Firms." *University College London Discussion Paper 95/19*, London, October.

Bureau van Dijk (2005) Amadeus – Company Directory Database, available also at www.amadeus.bvdep.com

Datastream (2006) Thomson Financial, www.datastream.com.

Gambardella, A., D. Harhoff, and B. Verspagen (2005), "The Value of Patents." Universita Bocconi, Ludwig-Maximiliens Universitaet, and Eindhoven University, Working Paper: http://www.creiweb.org/activities/sc_conferences/23/papers/gambardella.pdf

Gold, B. (1977), *Research, Technological Change and Economic Analysis*, Lexington Books, Lexington, Mass.

Graham, S. J. H. and D. C. Mowery (2003), "Intellectual Property Protection in the U. S. Software Industry," in W. M. Cohen and S. A. Merrill (eds.), *Patents in the Knowledge-Based Economy*, Washington, DC: National Academies Press.

Greenhalgh, C., and M. Rogers (2006), "The value of innovation: The interaction of competition, R&D and IP." *Research Policy* 35: 562-580.

Griliches, Z. (1979), "Issues in Assessing the Contribution of Research and Development to Productivity Growth." *Bell Journal of Economics* 10(1): 92-116.

Griliches, Z. (1981), "Market Value, R&D and Patents." *Economic Letters* 7: 183-87.

Griliches, Z. (1990), Patent Statistics as Economic Indicators: A Survey, *Journal of Economic Literature*, XXVIII (Dec.): 1661-1707.

Griliches, Z., Hall, H. B. and Pakes, A. (1991), "R&D, Patents. And Market Value Revisited: Is There a Second (Technological Opportunity) Factor?." *Economics of Innovation and New Technology* 1: 183-202.

Guellec, D. and B. Van Pottelsberghe de la Potterie (2000), "Applications, Grants, and the Value of Patent," *Economic Letters* 69 (1): 109-114.

Hall, B. H. (1993), The Stock Market Valuation of R&D Investment during the 1980s." *American Economic Review* 83: 259-64.

Hall, B. H. (2000), "Innovation and Market Value." In R. Barrell, G. Mason, and M. O'Mahoney (eds.), *Productivity, Innovation and Economic Performance*, Cambridge: Cambridge University Press.

Hall, B. H., and M. MacGarvie (2006), "The Private Value of Software Patents," Cambridge, Mass.: National Bureau of Economic Research Working Paper 12195 (April).

Hall, B. H., and Mairesse, J. (1995), "Exploring the Relationship between R&D and Productivity in French Manufacturing Firms," *Journal of Econometrics* 65: 263-94.

Hall, B. H., A. Jaffe, and Trajtenberg, M. (1998), "The Economic Significance of Patent Citations." UC Berkeley, Nuffield College, Brandeis University, University of Tel Aviv, mimeo.

Hall, B. H., A. Jaffe, and M. Trajtenberg (2001), "The NBER Patent Citations Data File: Lessons, Insights, and Methodological Tools." In A. Jaffe and M. Trajtenberg (eds), *Patents, Citations and Innovations,* Cambridge, MA: The MIT Press. Also Cambridge, Mass.: National Bureau of Economic Research Working Paper 8498 (October).

Hall B. H., A. Jaffe, and M. Trajtenberg (2005), "Market Value and Patent Citations," *Rand Journal of Economics* 36: 16-38.

Hall, B. H., and R. Oriani (2006), "Does the market value R&D investment by European firms? Evidence from a panel of manufacturing firms in France, Germany." *International Journal of Industrial Organization* 24: 971-993.

Hansen, L. P. (1982), "Large Sample Properties of Generalised Methods of Moments Estimators." *Econometrica* 50: 1029-1054.

Harhoff, D., F. Narin, and K. Vopel (1999), "Citation Frequency and the Value of Patented Inventions." *Review of Economics and Statistics* 81(3): 511-15.

Hoover's (2005), *Hoover's Company Directo*ry, www.hoovers.com.

Jolliffe, I T. (2002), *Principal Component Analysis*, Second Edition. New York: Springer-Verlag.

Lanjouw, J. O., and M. Schankerman (2004), "Patent Quality and Research Productivity: Measuring Innovation with Multiple Indicators." *Economic Journal* 114: 441-465.

Layne-Farrar, A. (2005). "Defining Software Patents: A Research Field Guide," LECG, Chicago: manuscript.

Lerner, J. (1994), "The Importance of Patent Scope: An Empirical Analysis," *Rand Journal of Economics* 25 (2): 319-33.

Levine, R. and Zervos, S. (1998), "Stock Markets, Banks, and Economic Growth." *American Economic Review* 88(3): 537-58.

Lindenberg, E.B. and S. A. Ross (1981), "Tobin"s q Ratio and Industrial Organisation." *Journal of Business* 54: 1-32.

Mansfield, E. (1968), *Industrial Research and Technological Innovation. An Econometric Analysis*. Norton, New York.

Montgomery, C.A. and B. Wernerfelt (1988), "Diversification, Ricardian Rents, and Tobin"s q." *Rand Journal of Economics* 19(4): 623-32.

Nelson, R.R. (1959), "The Simple Economics of Basic Scientific Research." *Journal of Political Economy* 67(June): 297-306.

Norsworthy, J. R. and S. L. Jang (1992), *Empirical Measurement and Analysis of Productivity and Technological Change. Applications in High-Technology and Services Industries*, North Holland, Amsterdam.

PATSTAT (2006), *EPO Worldwide Patent Statistical Database* – Available under license from OECD-EPO Task Force on Patent Statistics.

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

Teece, D.J. (1986), "Profiting from Technological Innovation: Implications for Integration, Collaboration, Licensing and Public Policy." *Research Policy* 15: 285–305.

Thoma G. and Torrisi S. (2005), "Evolution of Software Industry in Europe," *Study of the effects of allowing patents claims for computer-implemented inventions*, Brussels: EU DG Commission Research Report.

Toivanen, O., P. Stoneman, and D. Bosworth (2002), "Innovation and the market value of UK firms, 1989-1995." *Oxford Bulletin Of Economics And Statistics* 64: 39-___.

Wildasin, D. E. (1984), "The q Theory of Investment with Many Capital Goods." *American Economic Review* 74(1): 203-10

Appendix A – Additional Descriptive Statistics

Table A.1. Distribution by year of incorporation and market capitalisation

Year of incorporation	Market Capitalisation (million US$ - latest year available)									
	<100		100-1000		1000-5000		> 5000		All	
before 1970	45	14.2	54	22.9	41	45.1	45	51.1	185	25.3
1971-1980	10	3.2	18	7.6	9	9.9	5	5.7	42	5.7
1981-1990	58	18.4	51	21.6	15	16.5	16	18.2	140	19.2
1991-2000	160	50.6	95	40.3	23	25.3	15	17.0	293	40.1
after 2000	43	13.6	18	7.6	3	3.3	7	8.0	71	9.7
All	316	100.0	236	100.0	91	100.0	88	100.0	731	100.0

Table A.2. Distribution by stock market listing

Main Exchange	Companies	Share (%)
Euronext Brussels	1	0.1
Euronext Paris	57	7.8
Frankfurt Stock Exchange	58	7.9
London Stock Exchange (SEAQ)	225	30.8
London Stock Exchange (SETS)	155	21.2
NASDAQ National Market	7	1.0
NASDAQ OTC Bulletin Board	2	0.3
New York Stock Exchange	1	0.1
OFEX	1	0.1
Stockholm Stock Exchange	81	11.1
Swiss Electronic Stock Exchange	12	1.6
Swiss Exchange	51	7.0
XETRA	80	10.9
Overall	**731**	**100.0**

Table A.3. Distribution of companies by industry – 2.5 digit industry class

	with R&D		with patents		with software patents	
2,5 digit industry class	Companies	%	Companies	%	Companies	%
01 Food & tobacco	7	1.00%	3	0.64%	2	1.64%
02 Textiles, apparel & footwear	4	0.50%	3	0.64%	0	0.00%
03 Lumber & wood products	1	0.10%	1	0.21%	0	0.00%
04 Furniture	2	0.30%	1	0.21%	0	0.00%
05 Paper & paper products	7	1.00%	3	0.64%	0	0.00%
06 Printing & publishing	8	1.10%	5	1.07%	1	0.82%
07 Chemical products	24	3.30%	19	4.05%	8	6.56%
08 Petroleum refining & prods	7	1.00%	6	1.28%	3	2.46%
09 Plastics & rubber prods	15	2.10%	14	2.99%	1	0.82%
10 Stone, clay & glass	8	1.10%	6	1.28%	3	2.46%
11 Primary metal products	9	1.20%	5	1.07%	1	0.82%
12 Fabricated metal products	12	1.60%	6	1.28%	0	0.00%
13 Machinery & engines	46	6.30%	36	7.68%	14	11.48%
14 Computers & comp. equip.	23	3.10%	14	2.99%	5	4.10%
15 Electrical machinery	27	3.70%	19	4.05%	4	3.28%
16 Electronic inst. & comm. eq.	67	9.20%	48	10.23%	16	13.11%
17 Transportation equipment	6	0.80%	5	1.07%	4	3.28%
18 Motor vehicles	15	2.10%	15	3.20%	6	4.92%
19 Optical & medical instruments	33	4.50%	28	5.97%	3	2.46%
20 Pharmaceuticals	41	5.60%	35	7.46%	12	9.84%
21 Misc. manufacturing	17	2.30%	10	2.13%	1	0.82%
22 Soap & toiletries	9	1.20%	7	1.49%	3	2.46%
24 Computing software	117	16.00%	41	8.74%	10	8.20%
25 Telecommunications	15	2.10%	9	1.92%	4	3.28%
26 Wholesale trade	27	3.70%	20	4.26%	4	3.28%
27 Business services	29	4.00%	13	2.77%	0	0.00%
28 Agriculture	1	0.10%	1	0.21%	0	0.00%
29 Mining	4	0.50%	1	0.21%	1	0.82%
30 Construction	3	0.40%	2	0.43%	0	0.00%
31 Transportation services	3	0.40%		0.00%	0	0.00%
32 Utilities	16	2.20%	11	2.35%	2	1.64%
33 Trade	10	1.40%	4	0.85%	1	0.82%
34 Fire, Insurance, Real Estate	25	3.40%	11	2.35%	1	0.82%
35 Health services	6	0.80%	5	1.07%	0	0.00%
36 Engineering services	80	10.90%	59	12.58%	12	9.84%
37 Other services	7	1.00%	3	0.64%	0	0.00%
Overall	731	100.00%	469	100.00%	122	100.00%

Table A.4. Distribution of R&D, patents and software patents by industry

2.5 digit industry classes (731 firms)

	R&D in 1998		patents		software patents	
2,5 digit industry class	mil Euro	%	n	%	n	%
01 Food & tobacco	535	1.10%	1297	1.20%	8	0.50%
02 Textiles, apparel & footwear	1	0.00%	45	0.00%	0	0.00%
03 Lumber & wood products	0	0.00%	4	0.00%	0	0.00%
04 Furniture	4	0.00%	1	0.00%	0	0.00%
05 Paper & paper products	2	0.00%	21	0.00%	0	0.00%
06 Printing & publishing	340	0.70%	25	0.00%	1	0.10%
07 Chemical products	2573	5.30%	15755	14.20%	40	2.30%
08 Petroleum refining & prods	457	0.90%	1009	0.90%	15	0.90%
09 Plastics & rubber prods	15	0.00%	897	0.80%	2	0.10%
10 Stone, clay & glass	251	0.50%	794	0.70%	9	0.50%
11 Primary metal products	155	0.30%	307	0.30%	1	0.10%
12 Fabricated metal products	24	0.10%	189	0.20%	0	0.00%
13 Machinery & engines	765	1.60%	5147	4.60%	52	3.00%
14 Computers & comp. equip.	211	0.40%	881	0.80%	64	3.70%
15 Electrical machinery	1358	2.80%	3119	2.80%	58	3.30%
16 Electronic inst. & comm. eq.	7833	16.10%	31272	28.10%	1076	61.90%
17 Transportation equipment	796	1.60%	888	0.80%	19	1.10%
18 Motor vehicles	11661	24.00%	8601	7.70%	67	3.90%
19 Optical & medical instruments	106	0.20%	267	0.20%	4	0.20%
20 Pharmaceuticals	11214	23.00%	17492	15.70%	57	3.30%
21 Misc. manufacturing	79	0.20%	159	0.10%	2	0.10%
22 Soap & toiletries	527	1.10%	13080	11.80%	43	2.50%
24 Computing software	959	2.00%	550	0.50%	23	1.30%
25 Telecommunications	2453	5.00%	2163	1.90%	143	8.20%
26 Wholesale trade	316	0.60%	148	0.10%	7	0.40%
27 Business services	123	0.30%	221	0.20%	0	0.00%
28 Agriculture	2	0.00%	1	0.00%	0	0.00%
29 Mining	1	0.00%	93	0.10%	0	0.00%
30 Construction	30	0.10%	18	0.00%	1	0.10%
31 Transportation services	10	0.00%	0	0.00%	0	0.00%
32 Utilities	469	1.00%	2379	2.10%	24	1.40%
33 Trade	37	0.10%	129	0.10%	1	0.10%
34 Fire, Insurance, Real Estate	560	1.20%	462	0.40%	1	0.10%
35 Health services	27	0.10%	133	0.10%	0	0.00%
36 Engineering services	4782	9.80%	3487	3.10%	19	1.10%
37 Other services	0	0.00%	176	0.20%	0	0.00%
Overall	48676	100.00%	111210	100.00%	1737	100.00%

Table A.5. Descriptive statistics for R&D and non-R&D reporting firms

Variable	R&D reporting firms (731) Mean	R&D reporting firms (731) Number of observations	Non-R&D reporting firms (1736) Mean	Non-R&D reporting firms (1736) Number of observations	Significance Test of differences*
Tobin's q	2.90	2914	2.25	11103	***
Tangible fixed assets (M euros)	3720	2914	838	11103	***
Debt-tangible fixed assets ratio	1.47	2914	30.73	11103	
Sales (M euros)	3912	2906	1226	7624	***
Tangible fixed assets-sales ratio	0.54	2906	0.56	7597	
Labour cost-sales ratio	0.54	2495	0.35	7244	*
Dummy for control>33%	0.16	2914	0.34	11103	***

*Two-tailed two sample t-test: ***p<0.01; **p<0.05; *p<0.10

Appendix B – Correcting for citation truncation

The HJT method to identify the random process generating citations is based on the estimation of a semi-structural model which is made of two equations. With the first equation the citation frequency is modelled as a multiplicative function of cited-year effects (s), citing-year (t) effects, technology field (k) effects and citation lag effects (Hall *et al.*, 2001). The equation can be written as follows:

$$C_{kst} / P_{ks} = \alpha_0 \alpha_s \alpha_t \alpha_k \exp[f_k(L)]$$

where C_{kst} is the total number of citations received by patents with application date s and in technology k from patents with application date t. P_{ks} is the number of patents in technology k, year *s*. C_{kst} / P_{ks} is then the average number of citations received by patents *k-s* by all patents in year t. The parameters α_s, α_t, α_k measure the effect of, respectively, cited-year, citing-year and technology on the probability of citations. The function $f_k(L)$ describes the shape of the citation-lag (L=t-s) distribution, which is allowed to vary across fields. The multiplicative form of the citation frequency relies on the assumption of proportionality, i.e., the shape of the lag distribution is assumed to be independent of the number of citations received.

The α parameters are normalized so that each parameter measures the proportional difference in the citation propensity with respect to the base category. For instance, an estimated coefficient α_k= (*k*=chemicals field) = 2 implies that the expected citation rate of patents in the chemical field is twice the citation rate of patents in the base field.

The second equation in the model is the following:

$$f_k(L) = \exp(-\beta_{1k} L)(1 - \exp(-\beta_{2k} L)$$

where the parameters β_{1k} and β_{2k} measure the depreciation or obsolescence of the knowledge protected by patents in field k and the diffusion effect, respectively.

Following Hall et al (2001), we estimated this model by non linear least squares. Estimated α parameters can be used to remove cited-patent, citing-patent and technology field effects. Since we are primarily interested in truncation, we used the estimates of β parameters to calculate the expected distribution lags. Table B.1 reports the cumulative citation lag distributions in six large technological groups over the cited period 1978-2004. We used these proportions to correct the observed citation counts. Consider, for example, a chemical patent in year 2002 which has received 5 citations until 2005. Table B.1 shows that the typical chemical patent in year 2002 receives about 48.2% of citations after three years from its application. To correct for truncation we have to 'deflate' the observed citations by 0.48183 obtaining 10.38 citations.

The weights reported in Table B.1 are obtained by using all citations to EPO by year of cited patents, year of citing patents, citation lag and technological field of the cited patent. The source of data is PATSTAT (2006), which reports citations received by EPO patents from the main world patent offices, including the USPTO, the JPTO and the WIPO. Because of the large computation efforts required, we rely on the application year of EPO citing patents only, which account for about one-third of all citations received by EPO patents. Although the weights reported above have been estimated for this subset of citations only, we have used the same weights to correct all citations received by the patents in our sample, assuming that the shape of the simulated cumulative lag distributions does not vary with the citing patent's office. In future research we will collect information on non-EPO citing patents in order to relax this unrealistic assumption.

Table B.1. Simulated Cumulative Lag Distributions by Technology Field

cited year	lag	Chemical	Comp & communic.	Drugs & Medical	Electrical & Electronic	Mechanical	Other
2004	1	0.14108	0.12799	0.14654	0.13320	0.11821	0.11362
2003	2	0.31708	0.29223	0.32724	0.30222	0.27323	0.26416
2002	3	0.48183	0.45036	0.49442	0.46311	0.42574	0.41379
2001	4	0.61895	0.58574	0.63198	0.59932	0.55915	0.54602
2000	5	0.72601	0.69444	0.73813	0.70745	0.66859	0.65560
1999	6	0.80626	0.77825	0.81680	0.78990	0.75479	0.74280
1998	7	0.86479	0.84111	0.87352	0.85103	0.82082	0.81027
1997	8	0.90662	0.88730	0.91358	0.89546	0.87038	0.86144
1996	9	0.93605	0.92073	0.94147	0.92726	0.90700	0.89964
1995	10	0.95652	0.94463	0.96063	0.94973	0.93374	0.92781
1994	11	0.97061	0.96156	0.97368	0.96547	0.95308	0.94838
1993	12	0.98024	0.97344	0.98249	0.97641	0.96695	0.96328
1992	13	0.98677	0.98174	0.98841	0.98395	0.97683	0.97401
1991	14	0.99118	0.98750	0.99236	0.98913	0.98383	0.98168
1990	15	0.99414	0.99148	0.99498	0.99267	0.98876	0.98715
1989	16	0.99613	0.99421	0.99672	0.99507	0.99222	0.99102
1988	17	0.99745	0.99610	0.99786	0.99671	0.99465	0.99376
1987	18	0.99833	0.99738	0.99861	0.99780	0.99633	0.99569
1986	19	0.99891	0.99824	0.99910	0.99855	0.99751	0.99705
1985	20	0.99930	0.99884	0.99943	0.99905	0.99832	0.99799
1984	21	0.99955	0.99924	0.99964	0.99939	0.99888	0.99865
1983	22	0.99972	0.99951	0.99978	0.99961	0.99927	0.99912
1982	23	0.99983	0.99970	0.99986	0.99976	0.99954	0.99944
1981	24	0.99990	0.99982	0.99992	0.99986	0.99973	0.99966
1980	25	0.99995	0.99991	0.99996	0.99993	0.99985	0.99982
1979	26	0.99998	0.99996	0.99998	0.99997	0.99994	0.99993
1978	27	1.00000	1.00000	1.00000	1.00000	1.00000	1.00000

Appendix C – A Composite Patent Quality Indicator

The construction of the multidimensional measure of patent quality relies on factor analysis. In factor models each series of data (quality indicator in our case) is decomposed into a common component and an idiosyncratic component. The common component is only driven by a few common shocks, denoted by V< N, where N is the number of indicators. In a static factor model, the common shocks affect the indicators only contemporaneously. The basic model is given by $X = UB + E = K + E$, where X is the ($T \times N$) matrix of observations on N series (indicators) of length T. The series are normalized to have mean 0 and variance 1. U is the ($T \times V$) matrix of V common shocks and B is the (V $\times$ N) matrix of factor loadings, which determines the impact of common shock v on series n. The common shocks and the factor loadings together make up the common component K. After the influence of common shocks has been removed, only the idiosyncratic component (E) remains. To estimate the common component we have to find a linear combination of the indicators in X that explains as much as possible the total variance of each indicator, minimizing the idiosyncratic component (for a technical discussion of factor models see Jolliffe (2002).

The parallel with least squares estimation is clear from this formulation, but the fact that the common shocks are unobserved complicates the problem. The standard way to extract the common component in the static case is to use principal component analysis. In principal component analysis the first V eigenvalues and eigenvectors are calculated from the variance-covariance matrix of the dataset X. The common component is then defined as $K= XVV'$, with $V = [p_1,\ldots,p_V]$ and where p_i is the eigenvector corresponding to the ith largest ($i = 1 \ldots Q$) eigenvalue of the covariance matrix of X. This method does not ensure a unique solution. A further problem is that *ex ante* it is not known how many common shocks V affect the series in X. Following the approach suggested by Lanjouw and Schankerman (2004), we use a multiple-indicator model with an unobserved common factor:

$$y_{k\,i} = \lambda_k v_i + \beta' X + e_{ki}$$

where y_{ki} indicates the value of the kth patent indicator for the ith patent; v is the common factor with factor loadings λ_k and normally distributed, while X is a set of controls. The main underlining assumption is that the variability of each patent indicator in the sample may be generated by the variability of a common factor across all the indicators and an idiosyncratic component $e_k \sim N(0,\sigma^2_k)$ which is not related to other 'quality' indicators.

In our setting, the common factor is the unobserved characteristic of a patent that influences positively three 'quality' indicators: backward citations, forward citations, and the number of 8-digit IPC technology fields. The analysis is based on the total number of EPO patents granted between 1980 and 2001 (759,788 observations).

More precisely, to estimate q we followed a two step estimation procedure. In the first step we regressed by a three stage least squares estimator the three patent 'quality' indicators against two observable patent characteristics, i.e. the year of application and the main technology class of the patent (out of 30 macro-technological classes). Estimation of the common quality index v is then based on information extrapolated from the covariance matrix of three observable indicators. In the second step we estimated a factor model using the residuals from the first step by a maximum likelihood estimator, under the assumption that $q \sim N(0, \sigma^2)$. We found evidence of the existence of a single common factor only which we used as our multidimensional measure of patent 'quality' in the market value estimations.