Are Scientific Indicators of Patent Quality Useful to Investors?

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Are Scientific Indicators of Patent Quality Useful to Investors?

Abstract: Together with the number of patents and the value of R&D expenditures, scientific measures of patent quality give investors a useful basis upon which to judge the economic merit of the firm's inventive and innovative activity. Especially in the case of small cap and relatively low P/E high tech companies, we find a favorable stock-price influence when both the number of patents, the scientific merit of those patents, and R&D spending is high. Patent quality information also appears germane in the case of large cap high-tech companies with relatively high P/E ratios. In short, patent citation information may indeed help investors judge the future profit-earning potential of a firm's scientific discoveries.

Key Words: Patents, patent citations, market value, research and development.

JEL Classification: G12, G31, O31, O32.

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1. Introduction

Stock-price effects of corporate research and development (R&D) expenditures have been used to provide useful, albeit indirect, evidence on the economic consequences of the firm's inventive and innovative activity. For example, Chan, Lakonishok, and Sougiannis (2001) report that companies with relatively high R&D intensity tend to earn large excess returns. In a similar vein, Sundaram, John and John (1996) show that corporate research and development (R&D) spending announcements have predictably positive effects on the market value of the firm. These "predictive studies" document the ability of R&D expenditures to forecast future stockholder returns.

In a related line of research, called "association studies," researchers investigate the contemporaneous connection between stock prices and R&D intensity. Toivanen, Stoneman, and Bosworth (2002), and Chauvin and Hirschey (1993), among others, follow a long line of research to document evidence that R&D expenditures have large, positive and consistent cross-sectional influences on the market value of the firm. This is despite the fact that current accounting convention mandates an expense as incurred rather than capitalization treatment of R&D expenditures in the United States.[1] Like information on current cash flows, data on R&D spending appears to help investors form appropriate expectations concerning the size and variability of future cash flows. Corporate spending on R&D can be viewed as a form of investment in intangible assets with predictably positive effects on future cash flows. In a study of R&D expenditures, sales, and employment for some 1,000 large manufacturing firms during the 1957-77 period, Griliches (1986) confirms that privately-financed R&D expenditures have earned a relatively high rate of return on investment.[2]

Consistent with the fact that only a handful of firms is responsible for substantial R&D spending, positive stock-price effects of R&D are most evident in the case of large firms. Nevertheless, smaller firms are not precluded from making profitable investments in R&D. Hirschey and Spencer (1992) show that the well-targeted R&D efforts of the smallest firms can be highly profitable. While prior research strongly suggests that data on R&D spending helps investors form appropriate expectations concerning the magnitude and variability of future cash flows, these results give only indirect evidence on the stock-price effects of inventive output. This stems from the fact that R&D expenditures are a useful indicator of R&D *input,* whereas patents are a effective indicator of R&D *output* (see Griliches, 1990).

In this study, we seek direct evidence on the market value implications of inventive and innovative output by studying the association between stock prices and patent quality for firms of varying sizes and growth opportunities. In recent papers, Bloom and Van Reenen (2002) and Hirschey, Richardson, and Scholz (2001), extend a long line of research by documenting the fact that patents have an economically and statistically significant impact on firm-level productivity and market value, respectively. We posit that the stock-price effects of patent output will be most pronounced in the case of high-quality patents, where patent quality is measured by scientific merit. In a related study, Chung, Wright, and Charoenwong (1998) argue that the share price reaction to capital expenditure decisions depends critically upon the market's assessment of the quality of the firm's investment opportunities. They find that announcements of increases (decreases) in capital expenditures positively (negatively) affect the stock prices of announcing firms. With respect to capital expenditure announcements, it is the quality of the firm's investment opportunities that determines the share-price reaction to its capital expenditure decisions. Within the context of firm size and growth opportunities, we investigate the extent to which the stock market capitalization of inventive and innovative activity depends upon the quality of patent output produced.

Our paper is organized as follows. In section 2, the relevance of this study to prior research in financial economics is illustrated. Section 3 describes our data, model and estimation method. Empirical results are discussed in section 4. Section 5 states our conclusions and implications for future research.

2. Stock-price Effects of Patent Quality

2.1 Patents as Information

One of the most useful measures of the pace of inventive activity is the number of patents granted to a specific firm over a given time period, say one year. The widespread use of patent statistics stems from the fact that long-available patent data are derived from an objective and slow-changing standard. Under present law, the term of a U.S. patent is 20 years from the filing date of the patent application, or if reference is made to an earlier application, from the filing date of that earlier application. A wide body of economic research documents the strong relationship between patent numbers and R&D expenditures, and implies that patents are a good indicator of differences in inventive activity across firms (see Griliches, 1990). Unfortunately, while patent statistics remain a unique and valuable resource for studies of the process of technical change, problems are encountered when patents are used as a proxy for the pace of. inventive output at the firm level.

While all patents must meet objective criteria in terms of novelty and utility, not all patents have the same technical scope nor do they have the same economic significance. Patent scope depends on how inventions are linked to one another, and the extent to which rapid advances require a diversity of technical and nontechnical inputs. Whether or not a given patent has broad or narrow scope determines the ability of competitors to produce substitutes without fear of infringement suits, and helps define the amount of “monopoly power” enjoyed by the patent holder. Patents readily identifiable with end products tend to be more valuable than the average patent. Many low-value patents cover intermediate processes that, in themselves, do not lead directly to marketable products. Therefore, despite research that documents the generally robust positive effects of patent statistics on the market value of the firm, not all patents are created equal in the eyes of investors. In addition, important differences exist among firms in terms of their propensity to patent. There is no one-to-one relationship between R&D expenditures and patenting activity (see Griliches, Nordhaus, and Scherer, 1989).

In the early-1990s, Kortum (1993) noted that the patent-R&D ratio in the United States had declined steadily for over thirty years. At that time, some suggested that an exhaustion of technological opportunities had reduced the productivity of corporate R&D. Others argued that expanding world markets had raised the value of patents, and that growing competition in the research sector had resulted in greater R&D expenditures per patent. Like Griliches (1990), Kortum (1993) simply found that rising costs of dealing with the patent system had led researchers to patent fewer of their inventions. While industry data once supported the inference of a decline in the corporate propensity to patent, more recent data suggest the opposite. During the 1990s, there was an unprecedented surge in corporate patenting in the United States. Using both international and domestic data on patent applications and awards, Kortum and Lerner (1999) show that the recent jump in corporate patenting reflects an increase in innovation spurred by improvements in the strategic management of corporate R&D expenditures.

The use of patent statistics in economic research has been impeded by the fact that patents vary in their economic importance or value. Hence, simple patent counts are less than fully informative about the economic value of innovative output. Trajtenberg (1990) addressed this problem by examining the usefulness of patent indicators in the context of a particular innovation, Computed Tomography scanners, one of the most important advances in medical technology of recent times. As in prior studies, Trajtenberg (1990) found that simple patent counts are highly correlated with contemporaneous research and development expenditures. Interestingly, Trajtenberg (1990) also found a close association between citation-based patent indexes and independent measures of the social value of innovations in that field. Moreover, the value weighting scheme appears to be nonlinear in the number of citations, implying that the informational content of citations rises at the margin.

Albert, Avery, Narin, and McAllister (1991) sought early validation of citation counts as indicators of industrially important patents and found a strong association between citation counts for highly cited U. S. patents and knowledgeable peer opinion as to the patent's technical importance. A total of 20 researchers and research managers at Eastman Kodak Research Laboratories, all of whom are working in the area of silver halide technology, were asked to rate the technical impact and importance of each patent in overlapping sets of Eastman Kodak silver halide patents. A total of 77 patents were selected for rating. These patents ranged from those receiving zero citations to highly cited patents, or those patents which were cited 10 or more times on the front pages of subsequent U. S. patents issued through 1988. Among infrequently cited patents, there were no statistically significant difference between peer and citation ratings. In contrast, highly cited patents were rated far more important by the evaluators. As in the case of Trajtenberg's (1990) findings, the importance of cited patents appeared to increase more than proportionately with the number of citations.

In an effort to tie patent citations data to evidence of the economic merit of individual patents, Thomas (1999) analyzes the relationship between the technological impact of U. S. patents, as measured by patent citations, and the renewal decisions made by patent owners. A significant positive relationship is discovered across a number of time periods. The link between citations and renewals remains highly significant even after controlling for differences between internal and external citations, and differences in technology and patent ownership. In a related study, Harhoff, Narin, Scherer, and Vopel (1999) use a survey to obtain private economic value estimates for 964 inventions made in the U. S. and Germany, and on which German patent renewal fees were paid to full-term expiration in 1995. These authors find that patents renewed to full-term are much more heavily cited than patents allowed to expire prematurely. The higher an invention's economic value estimate, the more the patent was subsequently cited.

In a recent study, Deng, Lev and Narin (1999) tie current patent citation data to the firm's subsequent price-book ratios and stock-market returns. From price-book ratio regressions, Deng, Lev and

Narin (1999) conclude that the number of patents approved and patent citation data are strongly related to investor growth expectations in the chemicals, drugs and electronics industries. A somewhat weaker association between patent citation data and subsequent stock returns is reported. Hall, Jaffe and Trajtenberg (2000) report that firm market values are correlated with the portion of eventual citations that cannot be predicted based upon past citations. In other words, stock prices are correlated with future citations that cannot be predicted on the basis of current patent data. Hall, Jaffe and Trajtenberg (2000) conclude that the market "already knows" the information contained in future patent citations. In an interesting application, Breitzman and Thomas (2002),suggest that patent citation data can be fruitfully employed in targeting and valuing merger and acquisition candidates. In the due-diligence stage, patent citation analysis can be used to ensure that the target company's technology infrastructure is sound and that key inventors still work at the company. Patent quality analysis can also provide insight into the fit between the patent portfolios of the acquiring company and its acquisition target.

The purpose of this paper is to build upon this line of research by more fully investigating the importance of patent quality information for the market value of the firm. Specifically, we investigate the extent to which the stock-price effects of patent quality data are influenced by time-period, firm-specific and industry-specific influences. In so doing, we expand our understanding of the importance of patent quality information for investors that has been provided by Deng, Lev and Narin (1999) and Hall, Jaffe and Trajtenberg (2000). Industry-related effects may be especially important, given Cockburn and Griliches (1988) finding of an interaction between industry-level measures of the effectiveness of patents and the market's valuation of a firm's past R&D and patenting performance. We also build upon Trajtenberg (1990) and Albert, Avery, Narin, and McAllister (1991) by examining the importance of nonlinear influences of patent citation data on the market value of the firm.

2.2 The Scientific Merit of Patents

When a typical U.S. patent is issued, it has five or six prior U.S. patents cited on its front page that limit the claims of the patent being issued. If a patent is heavily cited in later patents, it is an indication that the earlier patent represented an important scientific advance. The “Citations Index” (*CI*) is the number of citations generated in the current year by patents granted to the company during the most recent five-year period, relative to the average number of citations for firms in a given International Patent Classification four-digit subclass and year.[3] Thus, *CI* measures how often a company's patent is cited in subsequent patent applications relative to the typical pace of patent citations for a given industry and year. A *CI* = 1 represents average citation frequency, *CI* = 2 means that a company's patents are twice as likely as average to be cited in subsequent patent applications. *CI* is a synchronous indicator reflecting five-years of patent activity. When a company's recent patents drop in impact, a decline in *CI* is noted during the current year. The *CI* is also helpful in that it involves a comparison among companies operating in the same general industry, at the same time, and with the same technology. This is important because patent citation frequency tends to vary widely from one industry and technology to another. *CIs* vary by technology. For example, *CIs* are high in semiconductors, biotechnology, and pharmaceuticals, and low in glass, clay & cement, and textiles.

Another measure of inventive output quality, called “Non-Patent References” (*NPR*), is predicated upon how closely a company's patents in the present year are to the scientific research base in the area. *NPR* is a simple count of the number of references in a patent application to a wide variety of non-patent publications, including scientific papers and articles, brochures, books, standards, documents, patent disclosure bulletins, and so on. On average, about one-half of all non-patent references are references to scientific articles. Of course, this varies by industry. Much more than one-half of biotechnology non-patent references are scientific in nature. Much less than one-half of non-patent references are scientific in nature for mechanical technologies, such as automotive and aerospace.

Science-based technologies such as chemistry, drugs and medicine have much higher *NPRs* than do mechanical technologies.

A third measure of patent quality is the "Technology Cycle Time" (*TCT*) indicator. *TCT* is the median age, computed in years, of the prior art references to earlier U.S. or European patents. For example, if a 1995 patent cited three patents, one from 1991, one from 1992 and one from 1993, the technology cycle time would be three years. For the firm as a whole, *TCT* represents the amount of time that has elapsed between current patents and the previous generation of patents. *TCT* is essentially a measure of cycle time between the current technology and a prior state of knowledge, measured from grant date to grant date. Emerging technologies have short cycle times, four years or less, whereas more mature technologies can display *TCT* that averages 15 or more years.

An emerging body of scientific research shows how patent citations relate to the scientific merit or “scientific quality” of inventive output. For example, Narin, Hamilton and Olivastro (1997) show the growing linkage between U.S. technology and public science by illustrating the increasing dependence over time of patented technology on scientific papers. In this paper, we consider the potential economic relevance of *CI*, *NPR*, and *TCT* indicators of patent quality. *CI* and *NPR* are technology impact indicators because they reflect the extent to which a firm’s patenting activity forms the basis for subsequent science. They are economic indicators to the extent that patents with high technological importance also have significant economic importance, and consistently positive effects on the market value of the firm. The expected economic life of a firm's patents is a positive function of *TCT* to the extent that the slow pace of historically slow-moving technology is a useful indicator of the speed of future invention and innovation. Positive stock-price effects of *TCT* represent a useful indication of the value tied to patent “durability.” Conversely, negative stock-price effects may be associated with *TCT* to the extent that “older” technology is highly subject to competitive inroads.

3. Data and Methodology

3.1 The Data

Patent statistics and patent citation information are obtained from Tech-Line® Company Patent Profiles, a technology indicators database marketed by CHI Research, Inc. (http://www.chiresearch.com/). Tech-Line® contains technological profiles on organizations actively patenting in the U.S., where each organization is responsible for at least 10 patents per year. By definition, this database focuses upon high-tech companies with active patent histories reflecting significant research and development, invention and innovative activity. Companies included in our analysis represent a sample from twenty-six major industry groups arrayed across the thirty technology areas defined by the IPC system. Industry groups with the heaviest representation include chemicals (55 companies), computer equipment (44), electronics (39), instrument and optical (32), and automotive (19). Our sample is taken from the 1989-95 period, and contains all Tech-Line® companies for which complete data could be obtained. A total of 1,720 firm-year observations for 267 public high-tech U.S. companies are included. This sample is sufficiently broad to permit a consideration of stock-price effects after controlling for the influence of industry and time period considerations. In all cases, year-end data are employed to ensure that patent quality measures are related to stock prices only during the period when such information is available for investors.

<Insert Table 1 about here>

Table 1 shows the quantity and scientific quality of U.S. patents for size group leaders using a simple three-part breakdown of the overall sample according to the market capitalization of common into “small” (market cap < $1.12 billion), “medium” ($1.12 billion < market cap < $3.71 billion), and “large” (market cap > $3.71 billion) high-tech companies. Firm averages over the 1989-95 period are reported to net out the effects of predictable year-to-year variation in each of these statistics. As shown in Table 1, giant high-tech firms dominate the list of firms awarded the greatest number of U.S. patents. These companies tend to be very rapid in their pace of improvement on patented technology. At the same time, medium and small U.S. companies also produce high quality patents, when quality is measured according to scientific merit. This means that U.S. companies of various sizes are noted for gaining patents that are widely cited in subsequent patent applications, academic journal articles and papers presented at scientific meetings. Based upon the data provided in Table 1, there is no clear distinction according to firm size in the quality of patents produced. It will be interesting to see if these scientific measures of patent quality are reflected in stock prices, and if such influences are affected by firms size.

In our empirical analysis, the market value of equity is the market price of common (*Compustat* variable A#24) times the number of shares outstanding (A#25) as of December 31 for each year. R&D expenditures (A#46) are obtained from annual income statements. Size effects in firm variables are normalized by deflating size-related variables (market value, number of patents, and R&D) by the book value of total asset (A#6) raised to the 1.5 power (or multiplying by $A^{-1.5}$), the log likelihood ratio minimizing deflator. Table 2 shows descriptive statistics for market-value and R&D data taken from *Compustat*, and for patent data from Tech-Line®.

Descriptive statistics are shown for the overall sample, and for a three-part breakdown according to firm size, as measured by market capitalization. Also shown are descriptive statistics for another simple three-part breakdowns of the overall sample according to growth opportunities, as captured by price-earnings (P/E) ratios. Table 2 shows that the typical high-tech firm in our sample is granted an average of 81.92 patents per year. Large market cap firms patent at a rate of 176.53 patents per year, or roughly seven and one-half times as much as the small cap firm average of 23.31 patents per year. Firm size plays an obvious role in determining the amount of resources available for inventive activity. Large cap firms spend an average $605.38 million on R&D per year, or roughly fourteen times as much as the $44.11 million spent by small cap firms in our sample.

Perhaps due to the obvious resource constraints facing smaller firms, small cap high-tech firms appear relatively more effective than large cap high-tech firms in terms of generating a relatively large number of patents for the amount of R&D expenditure. Among small cap firms, the R&D “cost” per patent appears to be roughly $1.89 million, while R&D cost per patent is $3.42 million among large cap firms. This relative cost effectiveness for small cap high tech firms exists despite no obvious size-based differences in patent quality. Note from Table 2 that a *CI* = 1.22 for small cap firms means that the patents produced by such companies are apt to be cited 22% more than average in subsequent patent applications. A *CI* = 1.07 for large cap firms suggests that their patents are apt to be cited only 7% more than average in subsequent patent applications. Similarly, the expected economic life of a firm's patents as captured by *TCT* seems marginally higher among small cap versus large cap high tech firms. Conversely, *NPR*, or the average number of "other references cited" on the front page of the patent, appears to be slightly higher among large cap versus small cap firms.

<Insert Table 2 about here>

In estimation, it will be interesting to note the extent to which the stock market perceives any size-based differences in the effectiveness of R&D and patent activity. Similarly, it will be interesting to note the extent that patent quality appears more important for firms with differing growth opportunities.

3.2 Model and Estimation Method

An increasing divergence between stock prices and fundamental factors, like earnings and book values, seems to imply a decline in the usefulness of traditional accounting information for security valuation in the high-tech sector. We consider the possibility that high-tech investors may need to supplement accounting information with nontraditional data that helps them form better estimates of the future profit-making potential of the firm's scientific endeavors. By considering the potential of stock-price effects tied to *CI*, *NPR* and *TCT*, we are open to the possibility that such data have economic usefulness.

Specifically, we consider a simple predictive equation for stock price changes where:

$$P_{i,t} = F\,(P_{i,t-1}\,,\ Patents_{i,t}\,,\ Patent\ Quality_{i,t}(CI_{i,t}, SL_{i,t}, TCT_{i,t}),\ R\&D_{i,t}, Earnings_{i,t}), \tag{1}$$

and $P_{i,t}$ is the present stock price, $P_{i,t-1}$ is the prior-year stock price. In this relation, notice that the cost of developing new patent output is reflected, at least in part, by current R&D expenditures. Notice also that the stock-price effects of ordinary physical assets and other such influences are reflected in $P_{i,\,t-1}$. It is well documented that earnings are among the main variables that affect stock prices. For this reason, current-period earnings are added as a control variable. We describe our model in very general terms to allow for some experimentation as to an appropriate empirical form. In contrast, Hall, Jaffe and Trajtenberg (2000) follow a long tradition of research on the economic implications of patenting activity by estimating a simple linear specification of their model. This traditional approach will be among those functional forms considered.

The focus of our interest is on how investors might use scientific indicators of patent quality as useful evidence concerning the future economic worth of the firm's patent activity. Under our main hypothesis, indicators of the scientific merit of patent output and R&D expenditures are expected to have a positive association with stock-prices. After allowing for the positive stock-price effects of patent quality, R&D expenditures might be expected to have a positive marginal stock-price influence because they shed further light on the scope of the firm’s inventive and innovative activity. In a sense, R&D expenditures can be viewed as a type of capital expenditure on intangible assets. Positive stock-price effects of R&D expenditures may also be observed to the extent that certain benefits of R&D are not directly tied to patent output. Of course, the positive intangible asset influences of R&D expenditures on firm stock prices may be partially offset by the fact that R&D expenditures also reflect the costs of developing valuable patents.

In measuring the stock-price effects of patent quality, we analyze a panel, or longitudinal, data set for the 1989-95 period. As is usually true in economics, the cross-section of units we analyze is much larger than the relatively brief number of time periods considered. Here, a *n* = 267 cross-section of firms is studied over seven (*t* = 7) time periods. Such a wide but short panel data set is more oriented toward cross-section analysis. Time effects are viewed as "transitions" or discrete changes of state. They are modeled as specific to the period in which they occur and are not carried across periods within a cross-sectional unit (or firm). Our primary focus is on heterogeneity across firms, which are the units of our analysis.[4] The fundamental advantage of such a panel data set over a simple cross section of data is that it allows greater flexibility in modeling differences in stock-price effects across firms.

In estimation we allow for the possibility that stock-price influences are specific to firms within individual industries. This method is responsive to Cockburn and Griliches' (1988) suggestion that the effectiveness of patents as a mechanism for appropriating the returns from R&D is not constant, but differs according to industry conditions. Our fixed effects approach involves the use of industry-specific constant terms in the regression model. This technique is sometimes referred to as a least squares dummy variable (LSDV) model, although the "least squares" part of the name refers to the means used to estimate the model, and not to the model itself (see Greene (2000, p. 560)). Our implicit assumption is that differences across industries can be captured by differences in the constant term. In principle, it is also possible to allow slope coefficients to vary across industries. However, given the large number of industries included, this method would involve a prohibitive cost in terms of lost degrees of freedom, especially in the case of subsamples arrayed according to firm size and growth opportunities. We also consider the possibility of time-period specific influences on stock prices. The matrix algebra and theoretical development of two-way industry and period effects in panel data models are quite complex. However, Baltagi (1995) shows that the practical application is relatively simple. Almost any application involving a second fixed effect can be handled by adding an additional set of dummy variables. In our empirical work, we estimate stock-price equations with fixed industry effects and fixed time period effects, and with fixed industry and period effects. For comparison, ordinary least squares (OLS) results without any allowance for fixed effects are also estimated. To control for the possibility of unspecified heteroskedasticity, we employ White's consistent estimators in all cases (see Greene (2000, p. 463)).

4. Estimation Results

4.1 Stock-price Effects

Table 3 contains the results for stock-price equations estimated with fixed industry effects, fixed time period effects, and fixed industry and time period effects. For comparison, OLS results without any fixed industry and period effects are also given. An underlying multiplicative functional form is hypothesized, so each model is estimated using OLS after using a natural logarithm transformation of each continuous variable. Implicit in this estimation is the idea that the marginal influence of each independent variable is contemporaneous and dependent upon the level of each other independent variable. Our approach is consistent with the hypothesis that the market quickly assesses the economic importance of the firm's patenting activity, and that the relationship between R&D expenditures and patenting is strongly contemporaneous, as reported by Hall, Griliches, and Hausman (1986).[5]

<Insert Table 3 about here>

As shown in Table 3, after controlling for patent quality, the number of patents granted during a year has a positive influence on stock prices. For the overall sample, it is reasonable to infer that the number of patents granted is an indicator of the economic worth created by the firm's inventive and innovative activity. This result is consistent with prior research, as is the finding of a predictably positive effect of R&D on stock prices. Positive stock price effects tied to the magnitude of R&D expenditures suggest that such spending gives rise to a type of intangible capital with important future benefits.

Of most direct interest to this study, Table 3 offers interesting evidence that patent quality statistics give investors a useful indicator of the economic merit of the firm's inventive activity. Notice that *CI*, which measures how often company patents are cited in subsequent patent applications relative to the typical pace of patent citations in an industry (and year), has consistently positive and statistically effects on stock prices in the overall sample. Moreover, positive stock-price effects of *CI* do not appear attenuated when significant industry and time period effects are controlled. *NPR*, which measures the average number of "other references cited" on the front page of a patent, has similarly positive and statistically significant influences on stock prices. As in the case of *CI*, positive and statistically significant stock price effects tied to *NPR* suggest that such information is incorporated by investors in their ongoing assessment of the firm's inventive and innovative activity. Like Hall, Jaffe and Trajtenberg's (2000), the positive link between stock prices and *CI* and *NPR* data implies that these data give investors a productive means for assessing the economic merit of the firm's patent activity. Our third measure of patent quality, *TCT,* measures the cycle time between current patents and the prior state of knowledge. The results suggest that *TCT* has a marginally positive influence on stock prices.

4.2 Effects of Size and Growth Opportunities

While Table 3 documents that the *CI* and *NPR* scientific measures of patent quality can be viewed as economically meaningful indicators of future profits tied to patent activity, it is not yet clear the extent to which such influences might vary by firm size and growth opportunities. To shed light on these important issues, Table 4 shows model estimation results after the overall sample has been partitioned according to market capitalization and firm P/E ratios.

When the overall sample has been partitioned according to market capitalization, important size-based differences in the stock-price effects of the number of patents and patent quality information are readily apparent.[6] In the case of small high-tech firms, positive stock price effects are tied to both the number of patents, the *NPR* and *TCT* indicators of patent quality, and the amount of R&D expenditures. Patent quality as captured by the *NPR* and *TCT* indicators may constitute especially useful information in the case of small high-tech firms that often have little in the way of reliable historical financial information. In the medium cap size class, investors appear to form appropriate expectations regarding the economic value of the firms' inventive and innovative output on the basis of the number of patents granted during the year, *TCT* and the level of R&D expenditures. In the large cap size class, investors appear able to form expectations regarding the economic value of the firms' inventive and innovative activity on the basis of patent numbers, *CI* and the *NPR* indicators of patent quality. Large high-tech firms tend to be prolific in the number of patents granted, and the *CI* and *NPR* indicators appears moderately useful in helping large cap investors decipher the importance of large-firm patent activity.

In a similar manner, important differences in the stock-price effects of patent quality information are apparent when the overall sample has been partitioned according to growth opportunities as reflected by firm P/E ratios.[7] The number of patents, the quality of patent output as captured by *NPR* and *TCT*, and R&D expenditures are all positively associated with stock prices for firms with low P/E ratios. Patent quality information captured by the *NPR* and *TCT* indicators also appears helpful in assessing the intangible assets of high-tech firms with relatively high P/E ratios. In the case of both moderate and high P/E firms, the *CI* indicator of patent quality also appears relevant. Interestingly, the number of patents has no independent market-value influence in the case of moderate and high P/E firms.

These findings add useful perspective to recent research by documenting the economic importance of scientific indicators of patent quality, and by showing how the relevance of such information is affected by firm size and the firm's growth opportunities. Based upon these results, patent quality information not only appears to be important in a scientific sense, it may also be helpful to stock-market investors seeking to assess the profit-making potential of the firm's inventive and innovative activity.

5. Conclusions

Investors often face the problem of making sensible judgments about future earnings prospects for high-tech companies with only limited earnings, revenue or book value information. This is especially true for high-tech companies with R&D programs that yield hard-to-evaluate patent output. This paper builds upon recent research to suggest the potential for scientific measures of patent quality as useful indicators of the future earnings potential for high-tech firms.

On an overall basis, we find that various scientific measures of patent quality have positive and statistically significant effects on stock prices. Together with the number of patents and the value of R&D expenditures, scientific measures of patent quality give investors a useful basis upon which to judge the economic merit of the firm's inventive and innovative activity. Especially in the case of small cap and relatively low P/E high tech companies, we find a favorable association between stock prices and the number of patents, the scientific merit of those patents as captured by the *NPR* and *TCT* patent quality indicators, and R&D spending. Patent quality information also appears germane in the case of large cap high-tech companies, where the *CI* and *NPR* patent-quality indicators have positive market value effects, and in the case of high-tech companies with relatively high P/E ratios, where the *CI*, *NPR* and *TCT* patent-quality indicators have positive market value effects. In short, patent citation information may indeed help investors assess the economic value of the firm's patent portfolio.

Footnotes

1. In the United States, the only exception to the "expense as incurred" rule for R&D pertains to software development costs which are capitalized and amortized over an estimated useful life. Aboody and Lev (1998) show that software capitalization-related variables are significantly associated with stock prices and future earnings and conclude that software capitalization summarizes information relevant to investors
2. Corporate spending on advertising and promotion and worker training, among other types of such expenditures, also has the potential to result in the creation of intangible assets. However, Chauvin and Hirschey (1997) show that while the total amount of money spent on corporate advertising and R&D is substantial, only a handful of firms devote significant amounts to *both* advertising and R&D. Given the high-tech manufacturing firms included in our sample, there is little reason to suspect any bias due to the omission of advertising data in this study of patent quality. We also found no evidence that the stock-price effects of patent quality are influenced by the pace of spending for capital equipment (results available on request).
3. In the calculation of *CI*, citations generated in the current year by patents granted to the company during the most recent five-year period are considered because this is the most comprehensive citations data available.
4. Baltagi (1995) offers a book-length survey on the econometrics of panel data, and includes an extensive bibliography.
5. Durbin-Watson test statistics suggest no autocorrelation among the least squares residuals for models reported on Tables 3 and 4. However, because the Durbin-Watson test can be biased toward a finding of no autocorrelation in the presence of a lagged dependent variable, we also considered Durbin's (1970) Lagrange multiplier test as an alternative to the standard procedure.

In each case, we fail to reject the null hypothesis of no autocorrelation (results available on request).

6. Estimating our valuation equation for each respective partition of the sample according to size and growth opportunities is equivalent to estimating simple slope-coefficient interactions between each independent variable and the size and growth dummy variables.

7. P/E ratios are a helpful and widely used indicator of the firm's growth opportunities. Growth opportunities can also be measured using P/B (price-book) ratios. Fairfield (1994) shows that the P/E ratio is a function of expected changes in future profitability, while the P/B ratio is a function of the expected level of future profitability. As a result, P/B ratios tend to correlate positively with future return on book value and P/E ratios tend to correlate with the rate of growth in earnings. We prefer to employ P/E ratios given our focus on future earnings growth, but qualitatively similar results are achieved using P/B ratios (results available on request).

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Table 1
Number of Patents and Patent Quality for Top High-tech Firms, 1989-95

Small Firms

Total Patents		Citations Index (*CI*)	
Unisys Corp	611	Actel Corp	5.35
Intl Specialty Prods Inc	333	Symbol Technologies	3.45
Zenith Electronics Corp	333	Norand Corp	2.80
Outboard Marine Corp	287	Collagen Corp	2.62
Cincinnati Milacron Inc	248	Ast Research Inc	2.62

Non-Patent References (*NPR*)		Technology Cycle Time (*TCT*)	
Immunex Corp	15.37	Immunex Corp	4.39
Mycogen Corp	4.62	Chips & Technologies	5.08
Dexter Corp	3.87	Ast Research Inc	5.57
Beckman Instruments Inc	2.65	Mycogen Corp	5.67
Bio-Rad Labs	2.64	Actel Corp	5.71

Medium-Size Firms

Total Patents		Citations Index (*CI*)	
Sundstrand Corp	891	Qualcomm Inc	4.78
National Semiconductor	807	Altera Corp	3.91
Ethyl Corp	656	Bard (C.r.) Inc	3.01
Tektronix Inc	653	Xilinx Inc	2.81
Advanced Micro Devices	625	Cordis Corp	2.72

Non-Patent References (*NPR*)		Technology Cycle Time (*TCT*)	
Genetics Institute Inc	11.55	Altera Corp	4.40
Union Camp Corp	6.26	Genetics Institute Inc	4.71
Stryker Corp	2.93	Xilinx Inc	5.06
Allergan Inc	2.92	Dell Computer Corp	5.13
Xilinx Inc	2.75	Advanced Micro Dev.	5.63

Large Firms

Total Patents		Citations Index (*CI*)	
General Electric Co	6576	Boston Scientific Corp	3.57
Intl Business Machines	6532	Sun Microsystems Inc	2.23
General Motors Corp	5740	Compaq Computer Corp	2.10
Eastman Kodak Co	5637	Intel Corp	1.96
Motorola Inc	4787	Medtronic Inc	1.92

Non-Patent References (*NPR*)		Technology Cycle Time (*TCT*)	
Genentech Inc	24.56	Sun Microsystems Inc	4.59
Chiron Corp	9.79	Intel Corp	4.86
Pioneer Hi-bred Intl	7.35	Micron Technology Inc	5.36
Weyerhaeuser Co	5.05	Apple Computer Inc	5.36

Lilly (Eli) & Co	4.60	Motorola Inc	5.56

Table 2
Overall Sample Stock Price EquationsWith Industry and Period Effects, 1989-95 (n = 1,720)

		Market cap ($millions)	Total assets	Number of Patents (*Patents*)	Citations Index (*CI*)	Non-Patent References (*NPR*)	Technology Cycle Time (*TCT*)	R&D expenditures (*R&D*) ($millions)	Earnings (*Earn*) ($millions)	Sample Size
a. Firm size (Market cap)										
Small (Market cap < $1.12 billion)	Mean	543.17	989.11	23.31	1.22	0.96	9.94	44.11	4.45	573
	Std. Dev.	300.47	1,095.48	23.14	0.87	2.33	3.96	66.26	111.67	
Medium ($1.12 billion < Market cap < $3.71 billion)	Mean	2,127.13	2,995.61	45.98	1.15	1.02	10.45	102.67	111.66	574
	Std. Dev.	714.39	3,622.47	43.84	0.85	2.48	3.47	126.48	129.59	
Large (Market cap > $3.71 billion)	Mean	16,330.40	15,116.28	176.53	1.07	1.27	9.59	605.38	853.02	573
	Std. Dev.	17,600.97	22,124.04	212.88	0.47	2.69	2.75	940.27	1,273.18	
b. Growth opportunities (P/E ratio)										
Low (*P/E* ratio < 12.11)	Mean	3,560.52	6,742.37	76.31	1.12	1.13	10.03	292.99	174.61	573
	Std. Dev.	7,043.81	17,760.49	139.32	0.71	2.71	3.79	802.25	893.97	
Moderate (12.11 < *P/E* ratio < 19.02)	Mean	8,250.39	7,522.52	99.12	1.07	0.83	10.07	268.77	528.13	574
	Std. Dev.	15,162.56	15,663.77	162.68	0.64	1.19	3.28	546.66	972.64	
High (*P/E* ratio > 19.02)	Mean	7,179.10	4,828.21	70.30	1.23	1.29	9.88	190.11	265.66	573
	Std. Dev.	13,031.62	7,470.57	122.87	0.89	3.16	3.24	382.78	513.56	
Overall Sample	Mean	6,331.12	6,365.04	81.92	1.14	1.08	9.99	250.63	322.92	1,720
	Std. Dev.	12,396.83	14,373.55	143.03	0.76	2.51	3.45	603.70	831.57	

Table 3
Overall Sample Stock Price Equations With Industry and Period Effects, 1989-95 (n = 1,720)

	OLS Model (no fixed effects)	Fixed Industry Effects	Fixed Period Effects	Fixed Industry and Period Effects
Independent variables				
Intercept	-0.021	-0.052	-0.029	-0.058
	(-1.52)^c	(-3.29)^a	(-2.02)^b	(-3.46)^a
Market value for prior period (P_{t-1})	0.339	0.327	0.347	0.335
	(5.44)^a	(5.18)^a	(5.48)^a	(5.23)^a
Number of Patents (*Patents*)	1.373	1.383	1.366	1.376
	(2.37)^a	(2.37)^a	(2.39)^a	(2.38)^a
Citations Index (*CI*)	0.023	0.024	0.022	0.024
	(3.79)^a	(3.82)^a	(3.61)^a	(3.70)^a
Non-Patent References (*NPR*)	0.010	0.008	0.009	0.007
	(4.07)^a	(2.48)^a	(3.53)^a	(2.01)^b
Technology Cycle Time (*TCT*)	0.006	0.010	0.006	0.010
	(1.26)	(2.10)^b	(1.30)^c	(2.13)^b
R&D Expenditures (*R&D*)	3.240	3.280	3.199	3.242
	(2.83)^a	(2.79)^a	(2.81)^a	(2.77)^a
Earnings (*Earnings*)	1.079	1.087	1.070	1.079
	(2.21)^b	(2.19)^b	(2.22)^b	(2.20)^b
Fixed effects (*F*- stat.)		1.69^b	5.16^a	2.44^a
R^2	86.5%	86.9%	86.8%	87.1%
F -stat. (entire model)	75.67^a	58.56^a	44.89^a	40.73^a

Notes: Dependent variable is market value for the current period (P_t).
All variables are entered using a natural log transformation (*t* -statistics in parentheses).

a indicates significance at the 1% level (one-tailed test).
b indicates significance at the 5% level (one-tailed test).
c indicates significance at the 10% level (one-tailed test).

Table 4
Overall Sample Stock Price EquationsWith Industry and Period Effects, 1989-95 (n = 1,720)

	Intercept	Stock Price for Prior Period (P_{t-1})	Number of Patents (*Patents*)	Citations Index (*CI*)	Non-Patent References (*NPR*)	Technology Cycle Time (*TCT*)	R&D expenditures (*R&D*)	Earnings *(Earn)*	R^2	*F*-stat.	Sample Size
a. Firm size (Market cap)											
Small (Market cap < $1.12 billion)	-0.097	0.294	1.451	0.012	0.018	0.013	3.320	1.123	89.3%	50.44^{a}	573
	(-2.66)^{a}	(3.84)^{a}	(2.40)^{a}	(1.07)	(2.12)^{b}	(1.39)^{c}	(2.06)^{b}	(1.97)^{b}			
Medium ($1.12 billion < Market cap < $3.71 billion)	-0.026	0.515	13.103	0.004	-0.002	0.009	6.957	3.063	80.8%	37.92^{a}	574
	(-2.05)^{b}	(5.99)^{a}	(4.91)^{a}	(0.78)	(-0.73)	(2.38)^{a}	(4.30)^{a}	(2.27)^{a}			
Large (Market cap > $3.71 billion)	0.012	0.320	23.609	0.014	0.007	0.005	-1.669	3.715	76.9%	59.58^{a}	573
	(0.66)	(3.40)^{a}	(2.31)^{b}	(1.69)^{b}	(2.02)^{b}	(0.83)	(-0.68)	(1.42)^{c}			
b. Growth opportunities (P/E ratio)											
Low (*P/E* ratio < 12.11)	-0.044	0.409	0.973	-0.001	0.016	0.015	2.372	0.485	92.8%	35.09^{a}	573
	(-1.53)^{c}	(3.53)^{a}	(2.36)^{a}	(-0.06)	(2.55)^{a}	(1.62)^{c}	(1.62)^{c}	(1.25)			
Moderate (12.11 < *P/E* ratio < 19.02)	0.001	0.006	0.671	0.002	0.000	-0.001	-1.146	14.691	97.5%	425.69^{a}	574
	(0.21)	(0.36)	(1.09)	(1.44)^{c}	(0.63)	(-1.13)	(-2.33)^{a}	(33.61)^{a}			
High (*P/E* ratio > 19.02)	-0.059	0.074	-0.258	0.031	0.006	0.014	4.126	17.328	85.7%	101.58^{a}	573
	(-3.95)^{a}	(1.87)^{b}	(-0.22)	(3.93)^{a}	(2.26)^{b}	(3.03)^{a}	(2.94)^{a}	(14.92)^{a}			

Notes: Dependent variable is market value for the current period (P_t).
All variables are entered using a natural log transformation (t-statistics in parentheses).

a indicates significance at the 1% level (one-tail test).
b indicates significance at the 5% level (one-tailed test).
c indicates significance at the 10% level (one-tailed test).