PATENT VALUE AND THE TOBIN'S *q* RATIO IN MEDIA SERVICES*

by

Kathryn Rudie Harrigan

Henry R. Kravis Professor of Business Leadership

Columbia University, 701 Uris Hall, New York, NY 10027 USA, 001-212-854-3494,

krh1@columbia.edu [*corresponding author*]

Maria Chiara DiGuardo

Associate Professor

University of Cagliari, Viale Fra Ignazio 74 – 09123, Cagliari, Italy, 039- 0706753360, diguardo@unica.it

JEL Codes: L10, L25, L29, L82, O31, O32

KEYWORDS: Backward citations; Tobin's *q*; radical invention; patent scores; innovation

* Suggestions were offered by Douglas Miller, Damon Phillips, Evan Rawley, David Ross and Andrea Prat. Research assistance was provided by Jesse Garrett, Donggi Ahn, Hongyu Chen, Elona Marku-Gjoka, the Patent Office of the Sardegna Ricerche Scientific Park and Thomson Reuters

This is a post-peer-review, pre-copyedit version of an article published in *The Journal of Technology Transfer.* The final authenticated version is available online at: https://doi.org/10.1007/s10961-017-9564-1

PATENT VALUE AND TOBIN'S *q* RATIO IN THE MEDIA-SERVICES INDUSTRY

Abstract

Changes in a firm's backward-dispersion patent-citation score are a useful, non-financial indicator of patent value that is positively-related to Tobin's *q*. *V-scores*, which analyze content patterns between patents' technological-class codes and those of their antecedents, provide contemporaneous information for investors to assess firms' economic prospects that is more time-sensitive than forward-looking information such as forward citations. V-score analysis offers useful insights about the nature of post-acquisition learning within technologically-tumultuous industries like media-services.

KEYWORDS: L10, L25, L29, L82, O31, O32

PATENT VALUE AND THE TOBIN'S *Q* RATIO IN MEDIA SERVICES

Patents represent valuable corporate resources which can reflect an inventive organization's potential to remain competitive by offering new (or improved) products. Prior-art citations (contained in patent examiners' reports) list the technologies which inventors have built upon in order to be granted a particular patent. The value created by patents arises, in part, from the organizational learning which their patented inventions embody. For investors, patents are positive indicators of a firm's future earnings potential (Bessen, 2009; Bosworth and Rogers, 2001; Hall, Jaffe, and Trajtenberg, 2005); clues about the nature of the firm's organizational learning may inform investors about the firm's future value.

Fleming (2001) and Fleming and Sorenson (2001) used focal patents' prior-art citations—including the age and frequency with which focal patents' technology-classification codes and combinations of other technology-classification codes occurred—to predict technological value (often termed "patent quality"), but they did not relate their results to the valuation of particular firms. Patent counts and numbers of cited prior-art patents were used by Hirschey, Richardson, and Scholz (2001) to help investors to assess specific firms' economic prospects (by assessing the market value of their R&D expenditures), but they did not use measures of the content patterns of patents' backward citations in their assessment of patent quality—although they did consider the relative newness of the backward-cited patents (which they counted as an additional indicator of patent quality), as did Sørensen and Stuart (2000) in their study of organizational aging and innovation. With these notable exceptions, much research concerning patent value has used patent counts or forward-looking, *future* prior-art measures to predict patent quality, *e.g.*, how many citations each patent has garnered from subsequent inventors (Aggarwal and Hsu, 2014; Hall, Jaffe, and Trajtenberg, 2005). Forward-looking, future prior-art citation analysis is a less-helpful indicator for investors because forward citations require time for a patent to amass (Jaffe, Trajtenberg, and Henderson, 1993)—which reduces their usefulness for investors as a contemporaneous, non-financial indicator of patent value.

Tobin's *q* (which compares a firm's market value to book value) reflects investors' expectations that are based upon then-available evidence. Information about patent content which is available at the time when such patents are granted (such as backward-looking, prior-art citation analysis) provides a more-timely prediction for investors about an organization's economic prospects than do forward-oriented measures of patent phenomena. This paper examines timely, non-financial indicators of patent value by analyzing the content patterns of their prior-art citations vis-a-vis a focal patent's grant. Our measure is a "backward-dispersion patent-citation score" that is similar in spirit to the *originality* measure of Trajtenberg, Henderson, and Jaffe (1997) because it emphasizes variance in the content of backward citations as they relate to the technology-class codes of a focal patent. We use the backward-dispersion patent-citation score (hereinafter called the *V-score*) to suggest expectations which investors may hold concerning the value of a patent's provenance as reflected in its Tobin's *q* ratio. Using acquisitions as a catalyst for finding potential novelty in combining firms' intellectual antecedents, we test the relationship of *V-scores* to investor expectations. We propose that patent-content patterns should be considered when predicting streams of future revenues that will be enjoyed when firms' patents are exploited commercially.

1.0.PATTERNS OF PATENT CONTENT

When a firm's market value rises or falls, its stock price fluctuations reflect the factoring in of newly-available information which affects investors' expectations of how well a firm will perform. Backward-citation analysis of patent content is an example of information which may be valuable for (but has not yet been widely applied to) assessing a firm's knowledge-based sources of advantage. If patents are indeed valuable corporate resources, they represent a repository of knowledge in which the inventive organization has invested. The record of a focal patent's prior-art citations—which is prepared by firms' lawyers and patent examiners in order to grant a patent's claims of novelty (Alcácer and Gittelman, 2006; Alcácer, Gittelman, and Sampat, 2009)—indicates the range of technological streams that were synthesized in order to create an invention. Comparison of a focal patent's granted claims with those of its knowledge antecedents (as evidenced by its *V-score* patterns) can suggest the relative novelty (for that particular firm) of its invention.

Our dependent variable, Tobin's *q*, is a measure which has been used to reflect investors' expectations concerning the value of firms' strategic decisions, *e.g.*, diversification strategy (Montgomery, 1982; Montgomery and Wernerfeldt, 1988), acquisitions (Anand and Singh, 1997; Lang and Stulz, 1994), or expectations concerning the quality of firms' resources, *e.g.*, "patent quality" (Chen and Shih, 2011). Because of the way in which focal-patent quality has largely been measured in the past (by looking forward—at users' citations—instead of looking backward for other patterns of value creation), studies which have related Tobin's *q* to focal-patent quality have inferred the value of the firm's patents by counting them, using proxies like the number of citations that a focal patent has received (*forward citations*) or calculating other forward-oriented measures of patent quality (Griliches, 1981; Hall, Jaffe and Trajtenberg, 2005). Forward citations may suggest the relative importance of an invention as a precedent for subsequent innovations; focal patents receiving many user citations have been built upon in many successive inventions—demonstrating the patent's usefulness or technological importance (Fleming, 2001)—and such inventions are sometimes called “gateway” or “high-quality” patents because they can garner substantial licensing fees or block subsequent economic activity if the knowledge that they control is not licensed out (Galasso and Schankerman, 2010; 2014; Lanjouw and Schankerman, 2001; Lemly and Shapiro, 2007; Serrano, 2010; Ziedonis, 2004).

1.1. Forward-Citation Analyses and External Users of Technology

Forward-looking analyses of patent value (such as those using counts of *future* prior-art citations) are tests of user efficacy; forward-citation counts offer evidence that patented knowledge has been built upon by independent researchers, as well as by the firm owning the focal patent (which Sørensen and Stuart (2000) termed “self-citing” patents). By looking forward, focal-patent value can be inferred from whether particular patent applications are renewed, or not (Harhoff, Narin, Scherer, and Vopel, 1999; Lanjouw, Pakes and Putnam, 1998), whether patent holders receive licensing rents in the form of royalties (Kamien and Tauman, 1986; Sherry and Teece, 2004) and at what price focal patents have been sold (Gambardella, Giuri, and Luzzi, 2007; Hirschey and Richardson, 2003; Nair, Mathew, and Nag, 2011; Serrano, 2010). Because patents can possess hold-up value if they are highly-cited, royalty revenues would increase if they were licensed (Bessen, 2009; Branstetter, Fisman and Foley, 2006; Lemley and Shapiro, 2007; Ziedonis, 2004).

Forward-looking measures, such as the number of forward citations that focal patents garner, are plausible discriminators of valuable patents because highly-cited patents are presumed to cover the gateway knowledge which subsequent patents must build upon (Fleming and Sorenson, 2001; Mariani, 2004; Nemet and Johnson, 2012). Future prior-art citations of patents have been used to indicate the presence of valuable resources (Miller, 2004; 2006), as a measure of focal patent quality (Hagedoorn and Cloodt, 2003; Hall, Jaffe, and Trajtenberg, 2001; Trajtenberg, 1990), as an indicator of knowledge flows—especially in spillovers (Danguy, De Rassenfosse, and Van Pottelsberghe de la Potterie, 2013; Jaffe, 1986; Jaffe, Fogarty, and Banks, 1998; Mowery, Oxley, and Silverman, 1996), as an indicator of the relative importance of a focal invention (Lee, Lee, Song, and Lee, 2007), and as evidence of firms' strategic intent (Lanjouw and Schankerman, 2001). The value of firms' "knowledge stocks" is frequently estimated by using absolute patent counts (Griliches, 1981; Hall, Griliches, and Hausman, 1986) or forward-citation counts (Hall, Jaffe, and Trajtenberg, 2001; 2005) and through these types of studies, the value of firms' knowledge stocks has been linked to market value.

The Tobin's *q* ratio reflects perceived value from focal-patent ownership as a stream of rents whose nature is initially unknown (without further information). Analysis of forward-citation counts may provide some additional information about earnings potential, but forward citations are notoriously skewed in their distribution (Bessen, 2009) because the top ten percent of all patents have garnered 48 percent to 93 percent of such financial payoffs (Scherer and Harhoff, 2000). Reliance on forward-citation indicators suggests that the market speculates about the promise of unknown future customers and values highly the most-cited patents—not the ones that prove to be most-widely cited by users from diverse technological streams (Hall, Jaffe, and Trajtenberg, 2005).

We tested "straw man" hypotheses to reflect the assumption that Tobin's *q* is sensitive to patent counts, especially to patents having many forward citations, and a negative relationship was found for all periods. The negative relationship persisted whether the patent count was based on a lagged seven-year count of patents or a cumulative count based on post-acquisition patents only. We found no support for the argument that investors seeking variously-timed returns would value firms having several patents more highly than firms who had only a few patents. We found no support for the argument that investors valued the number of forward citations that firms' patents received, but we found that the Tobin's q ratio was positively influenced by possession of highly-cited patents in the seventh year *after* an acquisition was consummated—suggesting that investors consider past patenting successes when valuing firms' futures. Ahuja and Lampert (2001) might argue that our research design did not allow enough time for forward-citation evidence to accumulate—which is a reasonable objection, except that our count was forward-biased to include all possible forward citations that were garnered for as many as twelve years while the bulk of forward citations typically occur shortly after a patent's grant (Jaffe, Trajtenberg, and Henderson, 1993).

We concluded from our "straw hypothesis" tests that having highly-cited patents represented market signals that firms have been innovative, but absolute patent counts did not have predictive value for investors in the case of media services. Forward citations of patents indicated the relative strength of the innovation signal as it pertained to forward-looking knowledge streams, but neither patent counts nor forward-citation counts proved to be useful contemporaneous data for predicting post-acquisition patenting performance. Forward-looking approaches to describing valuable focal patents—royalties, selling prices, and forward-looking, future prior-art citation measures—do not adequately capture the strategic potential of patents as being the type of organizational asset which can improve firms' competitiveness; they do not anticipate the effect of a patent's grant on higher shareholder returns. Forward-looking measures are *ex ante* and do not adequately capture the potential value that is created at the time when an organization learns how to integrate knowledge acquired from diverse technological cores and incorporate insights (which may be radical for them) into product offerings. Backward-looking, prior-art-citation information better indicates an organization's inventive prowess at the time of a patent's invention; the time-value of money favors performance indicators that are more contemporaneous than the duration of time that elapses before evaluations based on forward citations can be made. Using our *V-score* methodology, we examined whether investors would value firms more highly who had broadly expanded the diversity of knowledge which is synthesized in their patents.

1.2. Backward-Citation Analysis and Organizational Learning

The market values the possession of patents as a proxy for the underlying R&D activities in which firms have engaged (Bosworth and Rogers, 2001; Patel and Ward, 2011) and for other positive attributes associated with organizational learning. The granting of patents reflects an assignee's competence in a *core* technological field (Chen, 2010; Patel and Pavitt, 1997; Vanhaverbeke, Gilsing, Beerkens, and Duysters, 2009) and we treated the technology-class codes of a focal patent's grant as *core* in our analysis of the nature of organizational learning. Fleming (2001) established the value of incremental learning—that recombination of familiar components increases an invention's usefulness by enabling inventors to leverage past learnings and that combination familiarity facilitates the improvement of previous inventions (through incremental improvement). But Fleming (2001) also argued that novelty arises from those recombinations which were previously untried. The paucity of continuing investigation concerning the content of firms' patent antecedents is puzzling, given the ready availability of patent-examiner information and the importance of knowledge-based explanations of firm performance in understanding how organizations can create new knowledge to renew themselves (Felin and Hesterly, 2007; Grant, 1996; Kapoor and Lim, 2007). The richness of information available in the patent examiner's report can be mined extensively for meaningful measures of firms' knowledge-synthesis capabilities that could be of interest to investors (Roach and Cohen, 2013).

The backward citations that should be of greatest interest for predicting Tobin's *q* are those citations belonging to technology fields which are different from the technology-class codes where a focal patent has been granted; Trajtenberg (1990) referred to those types of prior-art citations as representing value that has been "spilled-over to other areas," and they are sometimes called out-of-the-box inventions because they integrate unexpected technological knowledge. For their characterization of focal-patents' antecedents, Trajtenberg, Henderson, and Jaffe (1997) created a weighted-dispersion index to score the breadth of sources that had been built upon by firms' focal patents (called "originality"), but it was not tested for its relationship to Tobin's *q*. Using their measure, Serrano (2010) found that the most "original" of a firm's focal patents tended to be cited by the broadest range of subsequent users (a characteristic that Trajtenberg, Henderson, and Jaffe, (1997) called "generality"), but Nemet and Johnson (2012) disagreed—finding that citations to external prior art were significantly *less* important to predicting future prior-art citations than were backward citations that were made in the same technology class as the focal-patents' class—a finding which would indicate that investors value *exploitation* of extant knowledge and local search more highly than *exploration* activity (March, 1991; Rosenkopf, and Nerkar, 2001; Lavie, and Rosenkopf, 2006).

Many technological fields have been converging in the post-Internet era; the technological evolution of providing online content has been affected by the novel recombinations that inventors are exploring, as have other Internet-facilitated industries. Although Nemet and Johnson (2012) found that the most-important inventions did *not* involve the transfer of new knowledge from one technological domain to another, there is merit in examining whether the market has valued patterns of knowledge cross-pollination.

2.0.TOBIN'S *q* AND EXPECTATIONS ABOUT PATENTS

The Tobin's *q* ratio (the ratio of market value to replacement value) can reflect whether investors expect higher future value creation—or have lower expectations of a firm's future prospects. The Tobin's *q* ratio indicates whether a firm's stock is currently overvalued (high ratio) or undervalued (low ratio). Its salience as a performance measure is reflected in the frequent charge to managers to maximize shareholder value through their discretionary decisions. As a forward-looking measure (reflecting investor expectations), Tobin's *q* considers future as well as current returns. Market hype and speculation may increase the ratio's numerator (an asset's current price), but the intellectual capital of corporations (their technology, organizational learning capacity, patent stocks, goodwill or other salient intangible assets) is not typically reflected in full in the ratio's denominator.

2.1. Tobin's *q* and Expectations about Patent-Content Patterns

Analysis of focal-patents' prior-art content provides information that knowledgeable investors could factor into their valuations of firms as soon as a patent examiner's report is issued (instead of waiting for information contained in forward citations of the focal-patent to become available). Because of the time-value of information, it is reasonable to expect that *V-scores* will show the greatest impact on investor expectations in the first years after a patent's award—before knowledge of a firm's inventive prowess becomes widely disseminated. *V-scores* offer evidence of firms' current inventive capabilities and may suggest higher future returns from the inventive learning processes underlying focal patents with higher scores.

The patents which have the strongest positive impact on investor expectations will be those showing evidence that a firm's inventors have successfully stretched beyond their core technological knowledge to incorporate novel, non-core knowledge in creating their patented inventions (instead of simply re-inventing within their traditional areas of core knowledge). Differences between the technology-class codes where a focal patent was granted and those which are cited as its technological precedents offer potential evidence that such patented inventions may be the types of innovations which could propel industry evolution and promote synergistic technological progress (Gambardella and Torrisi, 1998; Malerba, 2006; Mowery and Rosenberg, 1998; Nelson and Winter, 1982; Schumpeter, 1951) if their particular combination of technology precedents is efficacious for the problem that must be solved and they can extract rents from the products of their R&D outlays.

Patents which synthesize technological streams of knowledge in unexpected combinations may create precedents that other inventors would feel obliged to follow—thereby moving technological progress forward. In particular, inventions which are intended to respond to customer-initiated problems may require highly-resourceful technological solutions which result in the combining of ideas that must be gleaned from disparate knowledge streams where firms' inventors possessed low familiarity with dominant technologies and have had to stretch themselves to master salient technological aspects by learning about them. Investors will value possession of such patents more highly because they reflect organizational processes that recognize customer problems and exploits new knowledge in ways which lesser firms cannot easily emulate, thereby demonstrating competitive prowess. Incremental knowledge, such as the patent thickets which block the licensing of patents that others need to effect evolutionary technological change (Galasso and Schankerman, 2010), may not be valued as highly by investors because they are incremental.

2.1.1. Radical innovations. When solving unusual technological problems and creating products that deal with customers' needs, firms may go beyond their routine processes of knowledge exploitation—the local search process that facilitates incremental renewal of innovative capabilities—in order to blend the exotic types of technological insights that will facilitate creation of discontinuous inventions (Lin, Wu, Chang, Wang, and Lee, 2012; Makri, Hitt, and Lane, 2010). Sometimes termed "radical innovation" (Dahlin, and Behrens, 2005; Green, Gavin, and Aiman-Smith, 1995; Lettl, Herstatt, and Gemuenden, 2006; March, 1991; Schoenmakers, and Duysters, 2010), this search ability is itself a form of absorptive capacity that allows inventors to use external knowledge flows to improve innovative outcomes (Cohen and Levinthal, 1989; Escribano, Fosfuri, and Tribo, 2009; Volberda, Foss, and Lyles, 2010), accelerate response times (Benner, 2009; Goktan, and Miles, 2011), and institutionalize the ability to make radical innovations, when needed (Ahuja, and Katila, 2001; Cloodt, Hagedoorn, and Van Kranenburg, 2006; Nooteboom, Van Haverbeke, Duysters, Gilsing, and van den Oord, 2007; Tsai, 2009). Evidence that such discontinuous organizational learning has occurred can be found in the backward-citation patterns of focal firms' patents (which detail the pattern of technological fields that a patent has built upon as antecedents for its creation).

Out-of-the-box inventions are conceptually-similar to radical innovations because inventors must widen their search range beyond their traditional comfort level to reach their scientific solutions (Dahlin and Behrens, 2005; Garcia and Calantone, 2002; Green, Gavin, and Aiman-

Smith, 1995; Henderson, 1993; Lavie and Rosenkopf, 2006; Schoenmakers and Duysters, 2010). Radical inventions are the output of extreme exploratory activity (March, 1991; Rosenkopf and Nerkar, 2001) and can have a significant impact on firms' future revenue streams (Ahuja and Lampert, 2001). Transformative events, like the commercialization of the internet, often drive firms to blend novel technological approaches with their more-familiar solutions to address customers' problems—with the result of creating products that differed greatly from their past designs and functionality (Kelley, Ali, and Zahra, 2012); these inventions represented breaks with path-dependent learning routines.

Success in creating out-of-the-box inventions affects competence formation in relevant ways, such as the ability to synthesize inventions across seemingly-unrelated technology fields (Afuah and Bahram, 1995; Tripsas and Gavetti, 2000). Such successes could improve an inventive organization's absorptive capacity—thereby improving its subsequent ability to synthesize unfamiliar scientific knowledge with conventional solutions (Cohen and Levinthal, 1989; Kim, Song, and Nerkar, 2012). High *V-scores* indicate the award of focal patents having greater proportions of prior-art citations from technology classes that are different from the core areas of the focal-patent's grant.

2.1.2. Indicators of radical innovation. The inventions of greatest interest to investors are distinctive because their patent-content differ greatly from firms' incremental patents—which may have relied extensively on building within those technological areas which have constituted firms' areas of core expertise (or where firms have patented extensively in the past). *V-scores* are high when a large proportion of the technology-class codes assigned to prior-art patents are different from those assigned to firms' focal patents; the technology-class codes of the radical patents' antecedents are substantially different from those in which the focal patents' claims were granted. In those cases, firms whose patents have higher *V-scores* will be valued more highly by investors for the expectations that their pattern indicates if out-of-the-box innovation is re-warded.

The radical nature of inventions with high *V-scores* is amplified when the probability is low for particular combinations of technology class codes appearing together—especially when compared with the overall likelihood of their occurrence for all patents granted in a particular year. This anomaly is analogous to Fleming (2001)'s combination familiarity dimension which demonstrated negative and significant effects on his tests of dispersion. Even in cases where prior-art citations have originated with patent examiners instead of with the actual applicants (Alcácer and Gittelman, 2006; Sampat, 2010; Thompson, 2006), persistent patterns showing that unfamiliar, non-core knowledge has permeated focal patents' precedents would indicate that learning had occurred within inventive firms in ways that investors might value.

2.2. Using Acquisitions as a Benchmark Event

Tests of Tobin's *q* ratios are typically analyzed relative to an event (like an acquisition) in order to garner investors' reactions thereafter (Fulgieri and Hodrick, 2006; McWilliams and Siegel, 1997). The Tobin's *q* ratio at the time of the event (an acquisition) is specified as a control variable in predicting the directionality of future Tobin's *q* ratios and such longitudinal controls facilitate isolation of effects from subsequent events (such as post-acquisition integration of inventive organizations, learning from new colleagues and the subsequent development of additional capabilities which are reflected in patent content). All of the benchmark acquisitions we examined were made in the media services industry and exposed acquiring firms to varying degrees of new technological learning as the acquisitions were integrated.

In our tests of investors' reactions to potential changes in the patterns firms' focal patents' content, we expect that firms having prior experience with creating valuable inventions will possess greater capacity to recognize and consequently to absorb the types of novel, high-quality knowledge that is vital to creating subsequent valuable inventions in settings of technological tumult (Cohen and Levinthal, 1989). In particular, when two merged firms are technologically complementary, their post-integration research and development productivity can increase (Cassiman, Colombo, Garrone, and Veugelers, 2005) and evidence of such enhanced R&D capabilities may be positively recognized by the market (Dutta, Narasimhan, and Rajiv, 2005).

Inventions having exotic technological antecedents represent an important, unforeseen source of post-acquisition, revenue-enhancing synergy (Fulghieri and Hodrick, 2006); successful integration of acquisitions which generate combinatorial synergies of a type which would not typically be realized by the acquiring firms and their targets individually—and often cannot be anticipated (hence discounted by the market)—will be of interest to investors. By contrast, delays in amassing such post-acquisition performance improvements will compound the value being destroyed with the passing of time (Sirower, 1997); investors have been quick to penalize firms' market values if acquisition premiums paid have appeared to be unwarranted and offsetting benefits did not materialize quickly enough thereafter. Post-acquisition inventive capabilities that can be gained by mastering diverse and previously-unknown technological streams represent one of firms' best hopes for repaying acquisition premiums in a timely fashion and positively influencing investors' expectations regarding the resulting post-acquisition firm.

Hypothesis 1a: Patents having high backward-dispersion patent-citation scores (V-scores) will be valued more highly (as reflected by Tobin's q ratios) than patents with low V-scores.

Hypothesis 1b: Post-acquisition firms showing large increases in backward-dispersion patent-citation scores (V-scores) will be valued more highly (as reflected by Tobin's q ratios) than firms showing small (or negative) changes in their V-scores.

METHODOLOGY

Longitudinal information about the content of firms' focal patents and their Tobin's q ratios were obtained from Thomson Reuters' *Derwent Innovation Index* (2013b) and Standard and Poors' *COMPUSTAT* (2013) for the media-services industry from 1992 through 2012; acquisitions reported by Thomson Reuters (2013a) occurred within an eight-year window (from 1998 through 2005) that was chosen to capture the large-scale commercialization of the internet's potential. By 2005 the number of internet users had reached 1 billion and availability of media-providing services was an important driver of internet use.

3.1. Data and Sample

Media-services is a mixture of venerable, old media firms and young internet-content providers that represented 6 percent of U.S. gross economic output in 2013. Media-service providers held patents germane to how media is consumed by users; their inventions created the wherewithal for providing media content. Activities of media-service firms included print media, radio broadcasting, entertainment and informational content, and internet publishing, among others. Important technological innovations within the media services industry included solutions for video-centric networking, media streaming and cloud content delivery as well as conversion of firms' media libraries to electronic content; many of these innovations were commercialized after the internet bubble had burst. Thereafter the media services industry evolved to become the multimedia industry due, in part, to the convergence of different technologies that was occurring within the complementary telecommunications and electronics industries.

Thomson Reuters (2013a) reported acquisitions of 5,336 U.S. media firms; of those, 2,078 transactions were consummated during our research window (between 1998 and 2005). Incomplete financial data were available for 963 of the resulting firms; patents were granted to 329 firms. Because some firms made more than one media acquisition in a particular year under study, all data per firm was combined for each available year to yield 434 usable, reduced-set observations; 149 of those resulting firms held patents. Sample size decreased in post-acquisition years as acquiring firms were themselves acquired (or were no longer required to file financial statements—either because they went bankrupt or were taken private).

Patent report information for constructing the *V-Score* was gathered from U.S.-granted patents that were classified using the *Derwent Innovation Index* (Thomson Reuters, 2013b), which is a parsimonious classification system of 291 technology class codes that categorized patent documents for all affected technologies. Focal-patent information was collected at the firm level, not the laboratory level as Roach and Cohen (2013) did. Focal-patent genealogies (including prior-art citation codes) were taken from Thomson Reuters' *Web of Science* (2013c). We did not correct for self-citations to a focal patent when compiling its backward provenance.

3.2. Variables

3.2.1. Dependent variables. Tobin's *q* ratios were calculated for each year following the definition of Gompers, Ishi, and Metrick (2003): the market value of total assets divided by the book value of assets, where the market value of assets was computed as the book value of assets plus the market value of common stock less the sum of the book value of common stock and balance sheet deferred taxes. Tobin's *q* has been used to capture market expectations concerning intangible assets in many studies of patent valuation (Hall, Jaffe, and Trajtenberg, 2005; Patel and

Ward, 2011; Sandner and Block, 2011). Stock market volatility was expected to be highest during periods in the industry life-cycle when innovation was considered to be most "radical" (Mazzucato, 2002; 2003; Mazzucato and Tancioni, 2012). In our sample, average Tobin's *q* ratio values ranged from a high of 2.126 in 1999 to a low of 1.129 in 2011 with the highest standard deviations occurring when media-content firms like Martha Stewart, National Lampoon or Odyssey Pictures entered the sample (causing a dramatic run up in stock prices based on investor exuberance). Average Tobin's *q* values fell after the market had adjusted denominators for excessive acquisition premiums being paid (Graham, Lemmon, and Wolf, 2002). Our observation window included notable highs and lows in market valuations because—during the ensuing stock market run-up that was associated with the Internet bubble—firms booked accounting losses that resulted in negative equity values on their balance sheets, even as their market valuations soared (due to investor expectations concerning future returns).

3.2.2. V-scores as independent variables. Backward-dispersion patent-citation scores (*V-scores*) were calculated for each firm's focal patents in each year by comparing the variety of technology-class codes used to describe the claims of its antecedent patents with those describing the claims of the focal patent. Where Hall, Jaffe, and Trajtenberg (2001) used one United States Patent and Trademark Office (USPTO) technology-class code per focal patent, we used all available *Derwent* technology-class codes for each focal patent. Patent score, *V*, was equal to the weighted sum of the core score and non-core score—multiplied by a correction factor, $[\Sigma f_o/\Sigma f_i]$, which was the ratio of the count of outside-the-core technology-class codes divided by the ratio of the count of inside-the-core technology-class codes:

$$V = \Sigma([a_i, a_o \times ff_k]_k) \times [\Sigma f_o/\Sigma f_i]$$

where a_i and a_o are dyad weightings and ff_k is the frequency factor of each technology-class code$_{k.}$ Calculations were made in a spreadsheet matrix. Using the convention that i_n represented n- different inside-the-core technology-class codes that may appear in a patent and o_m represented m- different outside-the-core technology- class codes that may have been cited by that patent, we calculated the average dyad weighting, a_i or a_o, for each respective technology-class code as:

$$a_i = \Sigma p_j / i_n \text{ for inside the core (and } a_o = \Sigma p_j / o_m \text{ for outside the core)}$$

where p_j was the dyad weighting for a particular core (or non-core) technology-class code appearing with itself or with another backward-cited technology-class code and j equaled n times $(n + m)$. The technology-class code frequency, ff_k, was calculated as:

$$ff_k = f_k/F$$

where f_k was the frequency with which a technology-class code occurred in a particular patent and F was the sum of all technology-class codes appearing in that patent and k equals 1, 2, …, n, n+1, …, $n + m$. The frequency factor was multiplied times the average dyad rating per technology-class code and summed according to whether the precedent technology-class code was inside-the-core (cited code is the same as those awarded to the focal patent) or outside-the-core (cited code is different from those award to the focal patent).

The *V-score* calculation uses two weighting factors; it compares the *core* technology-class codes (i_n) of a focal patent's grant with those technology-class codes (o_m) that were assigned to its prior-art patents to determine the frequency with which each respective technology-class code appears in a patent examiner's report (f_k)—which is counted in order to derive its relative frequency weighting (ff_k). The relative frequencies (p_j) with which dyads of the granted technology-class codes occurred together (as a proportion of all U.S. patents that were granted in a particular year) provided the other weighting factor (a_i, a_o). *Web of Science* (2013c) provided frequency dyad information.

If all of the technology-class codes of backward-cited patents were the same as those describing the focal patent, the focal patent *V-score* was zero; yearly average *V-scores* were as high as 144.0 where the technology-class codes of backward-cited patents differed greatly from those of the focal patent. Our scoring approach is similar in spirit to co-occurrence measures that have been used to indicate the relatedness of the lines of business within diversified firms, such as the technology diversity index of Miller (2004) or other weighted estimates of distance (Bryce and Winter, 2009; Lien and Klein, 2009). In our sample, Pixar had the greatest absolute *V-score* for the observed years, but print-media companies—Reader's Digest, Times Mirror, and Tribune Company—had the highest *V-score* change scores.

3.2.3. Control variables. The Tobin's *q* ratio in year$_0$ (acquisition year) and logarithm of asset size (for each respective time period) were specified as controls in all tests to detect changes in investors' subsequent expectations as post-acquisition *V-scores* changed. Other controls included leverage, capital intensity, and binary variables reflecting possession of (a) media-content assets or (b) communications assets (to capture the effect of potential vertical integration). Diversification in the media sample was low (with a few notable outliers) as 41.5 percent of the acquirers remained single-business firms—even after making their "event" acquisition. Appendices I and II, which report the means and variance of variables used in our analysis, indicates the number of potential observations that were available for each variable in each year that was used in our specifications. The variance inflation factor was less than 2.0 for all variables tested in the specifications reported.

Appendix I and Appendix II at the end

3.0. SPECIFICATIONS AND RESULTS

Construction of variables showing *V-score* changes required annual averaged, focal-patent scores for two years (to calculate score differences); some firms patented infrequently, so the number of available observations was reduced. The lag which captured the greatest number of available patent observations was a two-year interval. Table 1 reports a positive and

----
Table 1 here
----

statistically-significant relationship between rising *V-scores* and the Tobin's *q* ratio for the three post-acquisition periods tested. The significance of the variable is stronger in the earlier-year specifications, although the sign remains positive for all specifications. The V-score's coefficient decreases (showing lesser statistical significance in the seventh post-acquisition year) which we interpreted as reflecting the diminishing impact of acquired knowledge that was reported by Ahuja and Katila (2001); attrition in the seventh year sample size may also explain results which suggest that *V-score* changes become a less-effective predictor of Tobin's *q* as time after the "event" acquisition passes. Media-content assets are weakly-negative immediately after firms are combined, but its sign reverses to weakly-positive by the seventh post-acquisition year and may suggest shifting investor emphasis on media-content assets by 2012. Communications assets are positive and significant as the number of post-acquisition years increase. The control variables were significant.

4.0. IMPLICATIONS OF RESULTS

V-score increases were associated with higher Tobin's *q* ratios; their significance diminished after seven years. The hypothesized relationship between them does not persist as time passes, but there is evidence to support Hypothesis 1b as results indicate that firms showing large increases in *V-scores* will be valued more highly than firms showing small (or negative) changes in their scores.

In the case of media services, there was great urgency for firms to monetize their print-library assets (by digitizing them) and devise ways of making media assets more accessible to consumers through a wide variety of distribution channels. The dominance of cable-broadband distribution as a conduit to reach customers increased and then decreased over the years studied. Given the great technological flux of the media-services industry, it is not surprising to find that successful media-service firms incorporated technological knowledge that was far afield of their core knowledge areas when monetizing their media assets between 1998 and 2012.

By 2007 many media-service firms were emphasizing software- and programming-content assets over distribution capabilities (thereby suggesting that content was king). Patents were typically awarded to devices while copyrights were awarded to movies and source codes. During the "credit freeze" era, investors may have weighted information about expenditures for copyrights more heavily than the inherently more-risky R&D outlays needed to patent inventions. The media-services industry was influenced by the changing strategic emphases of Time Warner and Comcast. Time Warner shed its cable operations and Comcast entered by acquiring the content-programming assets of Universal Studios and NBC; their approaches to providing media services varied greatly. The subsequent dominance of Netflix (who was not in our sample) suggests that access to media-content assets was important by 2012—even as the inventions used to deliver media content more effectively continued to be important to competitive success.

Stock prices fluctuate, in part, according to evidence of positive influences on firms' earnings potential. We have argued that investors will positively-value evidence that post-acquisition improvements in firms' inventive capacity has occurred. Changes in *V-scores* provide faster indications of post-acquisition, inventive activity than does the information contained in forward-citation counts. Analysis of outliers in *V-scores* may even suggest where a particular firm has patented inventions that could drive industry evolution in particular directions. Positive changes in *V-scores* are important signals for investors because they can indicate improvements in firms' mastery of new technologies.

Managers must consider investor expectations (as characterized by the Tobin's q ratio) because they need access to financing for their strategic decisions. Timely information with predictive value has become increasingly difficult to obtain in environments characterized by rapid technological change with potentially-disruptive technologies such as the media-services industry represents. The *V-score* represents one potential indicator of future returns that could be evaluated by investors.

Traditional indicators of patent quality—number of patents granted per year and forward-citation counts—were not significant predictors of post-acquisition Tobin's *q* for media-service firms. Forward-looking patent analyses appear to be of limited value in environments, such as the media-services industry, where it is difficult to forecast the length and thickness of forward-citation tails when patents are first granted. Positive returns have accrued to only 20 percent to 30 percent of research projects that have been undertaken in other industries (Silverberg and Verspagen, 2007); media services is a relatively new industry with traits that are not directly comparable to other types of research sites.

The approach of predicting returns based on content analysis of focal patents is a plausible alternative for investors to the real-options approach of betting on technological successes that firms employ (Bloom and Van Reenen, 2002). *V-scores* could be used to identify and reward firms for the possession of patents that have synthesized novel technologies into useful applications. All patents with high *V-scores* may not prove to be blockbusters, but persistent evidence of their intellectual quest to patent breakthrough knowledge demonstrates that innovating firms deserve access to funding. It would appear that important inventions do benefit from the transfer of knowledge from one technological domain to another and that investors value such organizational learning (as indicated by changes in the Tobin's *q* ratio over time).

References

Afuah, A.N., and N. Bahram, 1995, "The hypercube of innovation," *Research Policy*, 24, 51–76.

Aggarwal, V.A., and D.H. Hsu, 2014, "Entrepreneurial exits and innovation," *Management Science*, 60, 867-887.

Ahuja, G., and R. Katila, 2001, "Technological acquisitions and the innovation performance of acquiring firms: a longitudinal study," *Strategic Management Journal*, 25(8): 197-220.

Ahuja, G., and C.M. Lampert, 2001, "Entrepreneurship in large corporations: a longitudinal study of how established firms create breakthrough inventions," *Strategic Management Journal*, 22: 521–543.

Alcácer, J., and M. Gittelman, 2006, "Patent citations as a measure of knowledge flows: The influence of examiner citations," *Review of Economics and Statistics,* 88, 774-779.

Alcácer, J., M. Gittelman, and B. Sampat, 2009, "Applicant and examiner citations in U.S. patents: An overview and analysis," *Research Policy***,** 38, 415-427.

Anand, J., and H. Singh, 1997, "Asset redeployment, acquisitions and corporate strategy in declining industries," *Strategic Management Journal*, 18, 99-118.

Bessen, J. 2009, "Estimates of patent rents from firm market value," *Research Policy*, 38, 1604-1616.

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

Benner, M.J., 2009, "Dynamic or static capabilities? Process management practices and response to technological change," *Journal of Product Innovation Management***,** 26, 473-486.

Bosworth D., and M. Rogers M. 2001, "Market value, R&D and intellectual property: an empirical analysis of large Australian firms," *Economic Record*, 77, 323-337.

Branstetter, L.G., R. Fisman, and C.F. Foley, 2006, "Do stronger intellectual property rights increase international technology transfer? Empirical evidence from U.S. firm-level panel data, *Quarterly Journal of Economics*," 121, 321-349.

Bryce, D.J., and S.G. Winter, 2009, "A general interindustry relatedness measure," *Management Science,* 55, 1570-1585.

Cassiman, B., M.G. Colombo, P. Garrone, and R. Veugelers, 2005, "The impact of M&A on the R&D process―An empirical analysis of the role of technological- and market-relatedness," *Research Policy,* 34, 195-220.

Chen, Y.S. 2010, "Exploring the nonlinear effects of patent citations, patent share and relative patent position on market value in the US pharmaceutical industry," *Technology Analysis and Strategic Management*. 22, 153-169.

Chen, Y.S., and C.Y. Shih, 2011, "Re-examine the relationship between patents and Tobin's q," *Scientometric,* 89, 781-789.

Cloodt, M., Hagedoorn, J., and H. Van Kranenburg, 2006, "Mergers and Acquisitions: their effect on the innovative performance of companies in high-tech industries," *Research Policy,* 35, 642-668.

Cohen, W.M., and D.A. Levinthal, 1989, "Innovation and Learning: The Two Faces of R&D," *The Economic Journal,* 99, 569-596.

Dahlin, K.B., and D.M. Behrens, 2005, "When is an invention really radical? Defining and measuring technological radicalness," *Research Policy,* 34, 717-737.

Danguy, J., De Rassenfosse, G., and B. Van Pottelsberghe de la Potterie, 2013, "On the origins of the worldwide surge in patenting: an industry perspective on the R&D-patent relationship," *Industrial and Corporate Change*, 23, 535-572.

Dutta, S., O. Narasimhan, and S. Rajiv, 2005, "Conceptualizing and measuring capabilities: methodology and empirical application," *Strategic Management Journal,* 26, 277-285.

Escribano, A., A. Fosfuri, and J.A. Tribo, 2009, "Managing external knowledge flows: the moderating role of absorptive capacity," *Research Policy*, 38, 96-105.

Felin, T., and W.S. Hesterly, 2007, "The knowledge-based view, nested heterogeneity, and new value creation: Philosophical considerations on the locus of knowledge," *Academy of Management Review*, 32, 195-218.

Fleming, L., 2001, "Recombinant uncertainty in technological search," *Management Science*, 47, 117-132.

Fleming, L., and O. Sorenson, 2001, "Technology as a complex adaptive system: Evidence from patent data," *Research Policy*, 30, 1019-1039.

Fulgieri, P., and L.S. Hodrick, 2006, "Synergies and internal agency conflicts: The double-edged sword of mergers," *Journal of Economics and Management Strategy,* 15, 549-576.

Galasso, A., and M. Schankerman, 2010, "Patent thickets, courts, and the market for innovation," *RAND Journal of Economics*, 41, 472-503.

Gambardella, A., P. Giuri, and A. Luzzi, 2007, "The market for patents in Europe." *Research Policy,* 36, 1163-1183.

Gambardella, A., and S. Torrisi, 1998, "Does technological convergence imply convergence in markets? Evidence from the electronics industry." *Research Policy*, 27, 445-463.

Garcia, R., and R. Calantone, 2002, "A critical look at technological innovation typology and innovativeness terminology: a literature review." *Journal of Product Innovation Management*, 19, 110-132.

Goktan, A.B., and G. Miles, 2011, "Innovation speed and radicalness: are they inversely related?" *Management Decision*, 49, 533-547.

Gompers, P., J. Ishii, and A. Metrick, 2003, "Corporate governance and equity prices," *Quarterly Journal of Economics*, 118, 107-155.

Graham, J.R., M.L. Lemmon, and J.G. Wolf, 2002, "Does corporate diversification destroy value?" *Journal of Finance*, 57, 695-720.

Grant, R.M., 1996, "Toward a knowledge-based theory of the firm," *Strategic Management Journal*, 17, 109-122.

Green, S.G., M.B. Gavin, and L. Aiman-Smith, 1995, "Assessing a multidimensional measure of radical technological innovation," *IEEE Transactions on Engineering Management*, 42, 203-214.

Griliches, Z., 1981, "Market value, R&D, and patents," *Economic Letters*, 7, 183-187.

Hagadoorn, J., and M. Cloodt, 2003, "Measuring innovative performance: is there an advantage in using multiple indicators?" *Research Policy*, 32, 1365-1379.

Hall, B.H., Z. Griliches, and J.A. Hausman, 1986, "Patents and R&D: is there a lag," *International Economics Review*, 27, 265-283.

Hall, B.H., A.B. Jaffe, and M. Trajtenberg, 2001, "The NBER patent citations data file: lessons, insights and methodological tools," NBER working paper no. 8498.

Hall, B.H., A.B. Jaffe, and M. Trajtenberg, 2005, "Market value and patent citations," *RAND Journal of Economics*, 36, 16-38.

Harhoff, D., F. Narin, F.M. Scherer, and K. Vopel, 1999, "Citation frequency and the value of patented inventions," *Review of Economics and Statistics*, 81, 511-515.

Henderson, R., 1993, "Underinvestment and incompetence as responses to radical innovation: evidence from the photolithographic alignment equipment industry," *RAND Journal of Economics*, 24, 248-270.

Hirschey, M., and V.J. Richardson, 2003, "Investor underreaction to goodwill write-offs," *Financial Analysts Journal*, 59, 75-84.

Hirschey, M., V.J. Richardson, and S. Scholz, 2001, "Value relevance of nonfinancial information: The case of patent data," *Review of Quantitative Finance and Accounting*, 17, 223-235.

Jaffe, A.B., 1986, "Technological opportunity and spillovers of research-and-development - evidence from firms patents, profits, and market value," *American Economic Review*, 76, 984-1001.

Jaffe, A.B., M. Trajtenberg, and R. Henderson, 1993, "Geographic localization or knowledge spillovers as evidenced by patent citations," *Quarterly Journal of Economics*, 108, 577-598.

Jaffe, A.B., M.S. Fogarty, and B.A. Banks, 1998, "Evidence from patents and patent citations on the impact of NASA and other federal labs on commercial innovation," *Journal of Industrial Economics*, 46, 183-205.

Kamien, M.I., and Y. Tauman, 1986, "Fees versus royalties and the private value of a patent," *Quarterly Journal of Economics*, 101, 471-491.

Kapoor, R., and K. Lim, 2007, "The impact of acquisitions on the productivity of inventors at semiconductor firms: A synthesis of knowledge-based and incentive-based perspectives," *Academy of Management Journal*, 50, 1133-1155.

Kelley, D.J., A. Ali, and S.A. Zahra, 2013, "Where do breakthroughs come from? Characteristics of high-potential inventions," *Journal of Product Innovation Management*, 20, 1212-1226.

Kim, C.., J. Song, and A. Nerkar, 2012, "Learning and innovation: Exploitation and exploration trade-offs," *Journal of Business Research*, 65, 1189-1194.

Lang, L.H.P., and R.M. Stulz, 1994, "Tobin's q, corporate diversification, and firm performance," *Journal of Political Economy*, 102, 1248-1280.

Lanjouw, J.O., A. Pakes, and J. Putnam, 1998, "How to count patents and value intellectual property: The uses of patent renewal and application data," *Journal of Industrial Economics*, 46, 405-432.

Lanjouw, J.O., and M. Schankerman, 2001, "Characteristics of patent litigation: a window on competition," *The RAND Journal of Economics*, 32, 129-155.

Lavie, D. and L. Rosenkopf, 2006, "Balancing exploration and exploitation in alliance formation," *Academy of Management Journal*, 49, 797-818.

Lee, Y.G., J.D. Lee, Y.I. Song, and S.J. Lee, 2007, "An in-depth empirical analysis of patent citation counts using zero-inflated count data model: the case of KIST," *Scientometrics*, 70, 27-39.

Lettl, C., C. Herstatt, and H.G. Gemuenden, 2006, "Learning from users for radical innovation," *International Journal of Technology Management*, 33, 25–45.

Lemley, M.A., and C. Shapiro, 2007, “Patent holdup and royalty stacking,” *Texas Law Review*, 85, 191-2049.

Lien, L.B., and P.G. Klein, 2009, “Using competition to measure relatedness,” *Journal of Management*, 35, 1078-1107.

Lin, C., Y.J. Wu, C. Chang, W. Wang, and C.Y. Lee, 2012, “The alliance innovation performance of R&D alliances—the absorptive capacity perspective,” *Technovation*, 32, 282-292.

Makri, M., M.A. Hitt, and P.J. Lane, 2010, “Complementary technologies, knowledge relatedness, and invention outcomes in high technology mergers and acquisitions,” *Strategic Management Journal*, 31, 602-628.

Malerba, F., 2006, “Innovation and the evolution of industries,” *Journal of Evolutionary Economics*, 16, 3-21.

March, J.G., 1991, “Exploration and exploitation in organizational learning,” *Organization Science*, 2, 71-87.

Mariani, M., 2004, “What determines technological hits? Geography versus firm competencies,” *Research Policy*, 33, 1565-1582.

Mazzucato, M., 2002, “The PC industry: New economy or early life-cycle,” *Review of Economic Dynamics*, 5, 318-345.

Mazzucato, M., 2003, “Risk, variety and volatility: Innovation, growth and stock returns in old and new industries,” *Journal of Evolutionary Economics*, 13, 491-512.

Mazzucato, M., and M. Tancioni, 2012, “R&D, patents and stock return volatility,” *Journal of Evolutionary Economics*, 22, 811-832.

McWilliams, A., and D. Siegel, 1997, “Event studies in management research: theoretical and empirical issues,” *Academy of Management Journal*, 40, 626-657.

Miller, D.J., 2004, “Firms’ technological resources and the performance effects of diversification: a longitudinal study,” *Strategic Management Journal*, 25, 1097-1119.

Montgomery, C.A., 1982, “The measurement of firm diversification: some new empirical evidence,” *Academy of Management Journal*, 25, 299-307.

Montgomery, C.A., and B. Wernerfeldt, 1988, “Diversification, Ricardian rents and Tobin’s *q*,” *The RAND Journal of Economics*, 19, 623-632.

Mowery, D.C., J.E. Oxley, and B.S. Silverman, 1996, “Strategic alliances and interfirm knowledge transfer,” *Strategic Management Journal*, 17, 77-91.

Mowery, D.C., and N. Rosenberg, 1998, *Paths of Innovation: Technological Change in 20th-Century America,* Cambridge: Cambridge University Press.

Nair, S.S., M. Mathew, and D. Nag, 2011, "Dynamics between patent latent variables and patent price," *Technovation*, 31, 648-654.

Nelson, R.R., and S.G. Winter, 1982, *An Evolutionary Theory of Economic Change*, Cambridge: Belknap Harvard.

Nemet, G.F., and E. Johnson, 2012, "Do important inventions benefit from knowledge originating in other technological domains?" *Research Policy*, 41, 190-200.

Nooteboom B., W. Van Haverbeke, G. Duysters, V. Gilsing, and A. van den Oord, 2007, "Optimal cognitive distance and absorptive capacity," *Research Policy,* 36, 1016-1034.

Patel. D., and M.R. Ward, 2011, "Using patent citation patterns to infer innovation market competition," *Research Policy,* 40, 886-894.

Patel, P., and K. Pavitt, 1997, "The technological complexities of the world's largest firms: complex and path-dependent, but not much variety," *Research Policy*, 26, 147-156.

Roach, M., and W.M. Cohen, 2013, "Lens or prism? Patent citations as a measure of knowledge flows from public research," *Management Science*, 59, 504-525.

Rosenkopf, L., and A. Nerkar, 2001, "Beyond local search: boundary-spanning, exploration, and impact in the optical disk industry," *Strategic Management Journal*, 22, 287-306.

Sampat, B.N., 2010, "When do applicants search for prior art?" *Journal of Law and Economics***,** 53, 399-416.

Sandner, P.G., and J. Block, 2011, "The market value of R&D, patents, and trademarks," *Research Policy,* 40, 969-985.

Scherer, F.M., and D. Harhoff, 2000, "Technology policy for a world of skew-distributed outcomes," *Research Policy*, 29, 559-566.

Sherry, E.F., and D.J. Teece, 2004, "Royalties, evolving patent rights, and the value of innovation," *Research Policy,* 33, 179-191.

Schoenmakers, W., and G. Duy**ste**rs, 2010, "The technological origins of radical inventions," *Research Policy,* 39, 1051-1059.

Schumpeter, J.A., 1951, "The creative response in economic history," *Journal of Economic History*, 7, 149–159.

Serrano, C.J., 2010, "The dynamics of the transfer and renewal of patents," *RAND Journal of Economics,* 41, 686-708.

Silverberg G., and B. Verspagen, 2007, "The size distribution of innovation revisited: An application of extreme value statistics to citation and valuation measures of patent significance," *Journal of Econometrics*, 139, 318-339.

Sirower, M.L., 1997, *The Synergy Trap: How Companies Lose the Acquisition Game*, New York: Free Press.

Sørensen, J.R., and T.E. Stuart, 2000, "Aging, obsolescence, and organizational innovation," *Administrative Science Quarterly*, 45, 81-112.

Standard and Poor's, 2013, *COMPUSTAT Database*. New York: McGraw-Hill

Thompson, P., 2006, "Patent citations and the geography of knowledge spillovers: evidence from inventor- and examiner-added citations," *Review of Economics and Statistics*, 88, 383-389.

Thomson Reuters, 2013a, *SDC Platinum Database,* New York: Thomson Reuters.

Thomson Reuters, 2013b, *Derwent World Patents Index Classification Guide*, Philadelphia: Web of Science.

Thomson Reuters, 2013c, *Web of Science,* New York: Thomson Reuters.

Trajtenberg, M., 1990, "A penny for your quotes: patent citations and the value of innovations," *RAND Journal of Economics*, 21, 172-187.

Trajtenberg, M., R. Henderson, and A.B. Jaffe, 1997, "University versus corporate patents: a window on the basicness of invention," *Economics of Innovation and New Technology*, 5, 19-50.

Tripsas, M., and G. Gavetti, 2000, "Capabilities, cognition, and inertia: evidence from digital imaging," *Strategic Management Journal,* 21, 1147–1161.

Tsai, K.H., 2009, "Collaborative networks and product innovation performance: toward a contingency perspective," *Research Policy,* 38, 765-778.

Utterback, J., 1996, *Mastering the Dynamics of Innovation*, Boston, MA: Harvard Business School Press.

Vanhaverbeke, W., V. Gilsing, B. Beerkens, and G. Duysters, 2009, "The role of alliance network redundancy in the creation of core and non-core technologies." *Journal of Management Studies*, 46, 215-244.

Volberda, H.W., N.J. Foss, N.J., and M.A. Lyles, 2010, "Absorbing the concept of absorptive capacity: how to realize its potential in the organization field," *Organization Science,* 21, 931-951.

Ziedonis, R.H., 2004, “Don’t fence me in: Fragmented markets for technology and the patent acquisition strategies of firms,” *Management Science*, 50, 804-820.

Table 1
Effect of Changes in Patent scores on Tobin's q

	1 **Tobin's q** **1 year after** **(yearly scores)**	**2** **Tobin's q** **1 year after** **(yearly scores)**	**3** **Tobin's q** **4 years after** **(yearly scores)**	**4** **Tobin's q** **4 years after** **(yearly scores)**	**5** **Tobin's q** **7 years after** **(yearly scores)**	**6** **Tobin's q** **7 years after** **(4-year scores)**[3]
Intercept	**4.1272**	**3.8326**	**2.2301**	**1.9918**	**0.6080**	**0.9011**
	(0.9569)	(0.9923)	(0.4309)	(0.3930)	(0.2102)	(0.3950)
	***	**	***	***	**	*
Change in Backward	**0.0222**	**0.0238**	**0.0096**	**0.0105**	**0.0035**	**0.0085**
Patent Scores$_{t-2}$	(0.0075)	(0.0078)	(0.0042)	(0.0039)	(0.0023)	(0.0039)
	**	**	*	**	NS	*
Tobin's q in	**0.9112**	**0.8733**	**0.1722**	**0.1898**	**0.4439**	**0.2964**
acquisition year$_t$	(0.1509)	(0.1627)	(0.0502)	(0.0469)	(0.0480)	(0.0403)
	***	***	**	***	***	***
LogAssets$_t$	**-0.5498**	**-0.6799**	**-0.2862**	**-0.2733**	**-0.0567**	**-0.0689**
	(0.1915)	(0.2162)	(0.0846)	(0.0848)	(0.0434)	(0.0840)
	**	**	**	**	NS	NS
Leverage$_t$	**-3.9487**	**-2.3660**	**--**	**--**	**--**	**-1.9886**
	(1.3273)	(1.4054)				(0.7786)
	**	*				*

(Table 1 continued)	1 **Tobin's q 1 year after (yearly scores)**	2 **Tobin's q 1 year after (yearly scores)**	3 **Tobin's q 4 years after (yearly scores)**	4 **Tobin's q 4 years after (yearly scores)**	5 **Tobin's q 7 years after (yearly scores)**	6 **Tobin's q 7 years after (4-year scores)[1]**
Communication Assets$_t$	**--**	**0.1909** (0.4750) NS	**--**	**0.4514** (0.1951) *	**0.1791** (0.1089) NS	**0.3326** (0.1571) *
Content Assets$_t$	**-0.8873** (0.4688) †	**--**	**0.2261** (0.2269) NS	**--**	**--**	**0.3556** (0.2052) †
Adjusted R^2	**0.5242**	**0.4959**	**0.3398**	**0.3816**	**0.6231**	**0.5893**
Observations	60	59	77	76	60	61

*** <0.0001 ** 0.01 * 0.05 † 0.10

[1] Rolling, four-year averaged V-scores were subtracted from each other in order to increase the number of available observations to include those which were granted patents within a four-year time horizon.

Appendix I
Descriptive Statistics

		N	Mean	Std Dev	Minimum	Maximum
1	Tobin's q in $year_0$	378	1.74	1.39	0.10	15.48
2	Tobin's q in $year_1$	331	1.65	1.25	0.04	13.60
3	Tobin's q in $year_4$	394	1.49	0.89	0.15	6.98
4	Tobin's q in $year_7$	231	1.33	1.20	0.42	16.62
5	Change in Backward Citation Patent $Scores_{t-2}$	141	1.55	29.45	-113.33	76.32
6	$Logassets_1$	354	3.18	0.94	0.41	5.88
7	$Logassets_4$	400	3.15	1.03	-0.16	5.90
8	$Logassets_7$	250	3.39	0.94	-0.07	5.90
9	Assets per $Employee_1$	329	0.71	1.35	0.01	19.59
10	Assets per $Employee_4$	378	0.80	1.12	0.01	13.98
11	Assets per $Employee_7$	236	0.84	1.13	0.02	12.36
12	Long-term Debt/ $Assets_4$	378	0.80	1.12	0.01	13.98
13	Long-term Debt/ $Assets_7$	210	0.36	0.24	0.00	0.96
14	Number of Patents (7 years)	141	919.37	2799.00	0.00	13911.00
15	Forward Citations (7 years)	141	4096.00	14886.00	0.00	102420.00
16	Forward Citations / Patents	90	5.05	10.46	0.00	95.00
17	Communications Assets	434	0.57044	0.49559	0	1
18	Content Assets	434	0.52535	0.49993	0	1

Appendix II

Independent Variable Correlations, Significance and Number of Observations

		1	2	3	4	5	6	7
1	Tobin's q in $year_0$							
2	Change in Backward Citation Patent $Scores_{t-2}$	**0.06**						
		0.48						
		128						
3	$Logassets_1$	**-0.22**	**0.21**					
		<.0001	0.02					
		343	118					
4	$Logassets_4$	**-0.28**	**0.13**	**0.94**				
		<.0001	0.13	<.0001				
		358	134	339				
5	$Logassets_7$	**-0.12**	**0.14**	**0.92**	**0.93**			
		0.06	0.18	<.0001	<.0001			
		227	93	230	241			
6	Assets per $Employee_1$	**-0.06**	**-0.06**	**0.15**	**0.29**	**0.28**		
		0.30	0.57	0.01	<.0001	<.0001		
		325	109	329	315	213		
7	Assets per $Employee_4$	**-0.10**	**-0.18**	**0.25**	**0.35**	**0.22**	**0.69**	
		0.07	0.05	<.0001	<.0001	0.0007	<.0001	
		341	128	324	378	229	309	
8	Assets per $Employee_7$	**-0.10**	**-0.07**	**0.28**	**0.29**	**0.37**	**0.75**	**0.72**
		0.14	0.54	<.0001	<.0001	<.0001	<.0001	<.0001
		216	88	219	230	236	206	223

		1	2	3	4	5	6	7
9	Long-term Debt/ Assets4	**-0.16**	**0.10**	**-0.09**	**-0.11**	**-0.11**	**0.19**	**-0.08**
		0.00	0.25	0.11	0.04	0.09	0.001	0.16
		331	127	312	365	227	291	346
10	Long-term Debt/ Assets7	**-0.14**	**0.12**	**-0.16**	**-0.12**	**-0.29**	**0.28**	**0.42**
		0.05	0.33	0.02	0.10	<.0001	0.0002	<.0001
		193	71	195	205	210	181	196
11	Number of Patents	**-0.15**	**0.00**	**0.21**	**0.22**	**0.18**	**0.30**	**0.38**
		0.10	0.95	0.02	0.01	0.08	0.002	<.0001
		128	141	118	134	93	109	128
12	Forward Citations	**-0.06**	**-0.01**	**0.22**	**0.22**	**0.19**	**0.30**	**0.38**
		0.54	0.90	0.02	0.01	0.07	0.00	<.0001
		128	141	118	134	93	109	128
13	Forward Citations / Patents	**0.35**	**0.17**	**0.01**	**-0.05**	**0.02**	**0.36**	**0.08**
		0.001	0.11	0.94	0.68	0.87	0.002	0.51
		83	90	75	83	64	70	78
14	Communications Assets	**-0.04**	**-0.08**	**-0.03**	**0.10**	**-0.06**	**0.18**	**0.17**
		0.46	0.15	0.61	0.12	0.49	0.001	0.001
		377	330	393	231	140	353	399
15	Content Assets	**0.04**	**-0.02**	**0.11**	**-0.01**	**0.28**	**0.20**	**0.18**
		0.42	0.69	0.03	0.86	0.001	0.0001	0.0004
		378	331	394	231	141	354	400

		8	9	10	11	12	13
9	Long-term Debt/ Assets$_4$	**0.23**					
		0.001					
		217					
10	Long-term Debt/ Assets$_7$	**-0.08**	**0.38**				
		0.24	<.0001				
		200	203				
11	Number of Patents	**0.39**	**-0.23**	**-0.33**			
		0.0002	0.01	0.00			
		88	127	71			
12	Forward Citations	**0.39**	**-0.15**	**-0.15**	**0.81**		
		0.0002	0.09	0.21	<.0001		
		88	127	71	141		
13	Citations / Patents	**0.22**	**-0.02**	**0.19**	**-0.01**	**0.05**	
		0.10	0.85	0.21	0.95	0.65	
		59	79	45	90	90	
14	Media Distribution Pipes (binary)	**0.13**	**0.16**	**0.07**	**0.16**	**0.02**	**0.02**
		0.03	0.00	0.16	0.01	0.72	0.66
		250	328	377	236	367	433
15	Electronic Media (binary)	**0.26**	**-0.04**	**0.03**	**0.00**	**-0.16**	**0.32**
		<.0001	0.45	0.59	0.96	0.002	<.0001
		250	329	378	236	368	434

Coefficient
Significance level
Observations