Backward Dispersion Measures and Out-of-the-Box Inventions

by

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Abstract

Using a scoring methodology that is a refinement over the Trajtenberg, *et al* (1997) indices, we found that the financial performance measures of communications services firms having patents which synthesized highly-diverse technological knowledge streams had positively correlated patterns with scores for backward-cited antecedents. Alarmingly, tests of the relationship of Tobin's q measures with the backward-dispersion citation scores indicated that a negative relationship exists -- a result which may indicate that investors are not as eager to bet on the rewards of out-of-the box inventions as management is.

Keywords

Backward citations; Radical innovation; Patent scores; Derwent Innovation Index (DII)

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Highlights

- Scores for diversity of backward-cited patents were built for firms using different methodologies
- Results for methodologies were compared with financial performance measures
- Extant score methodology had negative relationship with ROA; our scores had positive relationship
- Positive relationship with ROS, but extant score methodology was not consistently significant
- Negative relationship with Tobin's q for both approaches, but straw man was not always significant

Backward Dispersion Scores and Out-of-the-Box Inventions

1. Introduction

Pleas for organizational creativity often invoke the need for out-of-the box thinking to synthesize solutions by drawing from disparate knowledge streams. It is thought that allowing inventors to combine ideas from diverse technologies serendipitously may yield fruitful approaches to solving customer needs. The idea is not foolproof since efforts to create inventions from unusual knowledge antecedents may impair short-term profitability and may not be highly valued by investors who are seeking immediate gratification. Nevertheless the blending of ideas from diverse technological families is considered to be a desirable activity and we investigate whether having a greater proportion of out-of-the-box patents is rewarded.

Industries facing rapid technological evolution are presumed to progress because firms within them have invented radically-new products – inventions which were often developed after exposure to knowledge outside their local domains (March and Simon, 1958; Nelson and Winter, 1982). Although radical inventions are much researched (Dahlin and Behrens, 2005; Henderson, 1993; Lavie and Rosenkopf, 2006; Schoenmakers and Duysters, 2010), there is no consistent delineation of what constitutes radical innovation (Garcia and Calantone, 2002; Green, *et al*, 1995). We refer to out-of-the-box inventions as being those types of radical inventions which are different in their antecedents from a firm's existing technologies because their backward-citation patterns differ greatly from that of a firm's core expertise. Our emphasis on backward citations is developed in a manner that is consistent with the significantly-larger body of literature about radical innovation which relies upon forward-citation patterns as its criterion. If inventions that are identified as being out-of-the-box based on backward citation measures prove also to be high-impact innovations based on forward citation measures (Ahuja & Lampert, 2001), their respective forward-dispersion patterns would indicate relevance to a widely-dispersed audience of subsequent innovators when using a methodology similar to that which we describe.

Out-of-the-box inventions may be evidence of exploratory innovation processes which create new technologies (Henderson, 1993; Kim, et al, 2012; March, 1991; Sorensen & Stuart, 2000). Exploratory inventions sometimes reflect patterns of exogenous technological confluence that presage important industry changes (Schoenmakers & Duysters, 2010), but their impact when calculating firms' patent scores may also reflect acquisitions that have been made as an alternative to the type of localized learning processes which exploit a firm's extant competencies. If an innovation substitution effect occurs following acquisition (Hitt, *et al*, 1990), the score of a firm's backward dispersion pattern of technological antecedents will likely spike after an acquisition and then decline and/ or converge over time to show a pattern closer to the firm's historical core of expertise – assuming that it continues to engage in inventive processes in-house thereafter.[1] If instead an acquisition is synergistic, a firm's backward dispersion scores would presumably increase over time to reflect the complementarity enjoyed after integration has occurred (Miller, et al, 2014).

To incorporate novel technological combinations into ongoing product lines, firms' innovation activities leading to patents cannot be merely incremental (Rosenkopf & Nerkar, 2001). Depending upon the extent of inventors' exposure to distant technologies and the nature of their investigative processes (i.e., whether they learned about new technologies via acquisition or solved their technological problems internally), firms may develop in-house, exploratory expertise for synthesizing distant technologies in their subsequent inventions (Cohen & Levinthal, 1990) or they may acquire expertise from outsiders. Regardless of how they gain exposure to novel technology streams, high backward dispersion scores – reflecting the initial assimilation of radical knowledge into their patents -- will characterize the patents of out-of-the-box inventions. As their search for ideas becomes more incremental – perhaps because inventors build upon the knowledge that originated from their past out-of-the-box inventions -- backward dispersion scores for subsequent inventions in that same research stream will likely decline to reflect a pattern of synthesis of more-familiar technologies.

[1] Similarly Killing's (1983) evidence of a research-substitution effect among firms that grew through joint ventures or strategic alliances suggests that firms who grow through alliances or acquisitions may reduce subsequent innovation efforts thereafter.

We examined the effect of out-of-the-box inventions on firm performance by using patent citations to construct year-by-year backward dispersion scores (which are averaged measures representing the mix of technological class codes found in antecedent patents that were cited by examiners in each application for which a patent was ultimately granted). Two methodologies were used to construct these dispersion scores – the Hall, *et al* (2001) counting method which used an abbreviation of the USPTO technology class codes and a distance score which used the classification system of the Derwent Innovation Index. We compare the respective efficacy of these year-by-year backward dispersion scores as predictors of a firm's financial performance measures using examples from the communications services industry during a period of time when voice, video and data communications were experiencing rapid technological changes and radical inventions were more likely to be included among a firm's annual patent portfolio.

2. Backward dispersion scores

Backward dispersion scores represent the range of technological class codes cited in a patent application, with particular interest in class codes that are different from the patent's core technological class codes. They are a characterization of a patent's pedigree. When a patent is granted, the Patent Office accepts the applicants' technological claims of novelty only after searching through germane intellectual antecedents for evidence of precedents. The technology class codes in which a patent's claims are granted represent its *core* technology (Leonard-Barton, 1992); a patent's cited antecedents can have codes similar to or diverse from the technology class codes that are assigned when a patent is ultimately granted. Those codes which are different from the technology class codes assigned to a patent are considered to be *non-core* codes (Bapuji, et al, 2011).

The breadth of knowledge that a particular invention has synthesized can be quantified by weighting the patent examiner's backward citations to create a score that considers the similarity to (or dissimilarity of) the backward-cited precedents as compared with those assigned to the patent. The score is intended to characterize the patent's technological roots. Since inventors can claim patent rights only for the unique aspects of their inventions, the backward patent-citation requirement establishes the scope of a patent under examination; the diversity of technological class codes extended by an invention's claims reflects the range of knowledge bases that the inventors are conversant in.

Synthesis of divergent ideas may become less basic as generations of inventions build upon the same pattern of synthesis and so, to the extent that a firm's patent synthesizes knowledge from pre-existing art in technological classes that are different from those in which the patent's claim is granted, a patent may be classified as a boundary-spanning invention (Banerjee and Cole, 2010; Rosenkopf and Nerkar, 2001; Tushman and Scanlon, 1981) -- if the pattern of cited precedents is indeed unusual. The dispersion pattern of cited technology class codes should not be considered extraordinary, however, if it is the same pattern of seemingly-divergent cited codes as are the technology class codes of the granted patent.

2.1 Counts and distance measures

Trajtenberg, Henderson and Jaffe (1997) suggested that citation counts of the different technology code classifications of the United States Patent and Trademark Office (USPTO) could be used to measure the broadness of an invention's technological roots. Their measure, called "original" represented the breadth of technological knowledge foundations that were synthesized in patent applications. The Trajtenberg, *et al* (1997) measure summed the squared proportions of backward citations which belonged to diverse technological classes (measured as a proportion of total technological classes). Hall, Jaffe and Trajtenberg (2001) operationalized this backward citation measure using a simplified classification scheme that collapsed the 426 extant USPTO patent classes (representing over 120,000 patent subclasses) into six technological categories and thirty-six subcategories in order to create a manageable system for making comparisons. Briefly, their measure was similar to a Herfindahl-Hirschman index (Herfindahl, 1950; Hirschman, 1945; 1964; Rosenbluth, 1955) whereby the counts of each cited subcategory provided weightings for the squared and summed raw scores which were subtracted from 1.00 to produce their score.

The score produced by Hall, *et al* (2001)'s counting methodology does not distinguish well among patents with differently-distributed citations as Exhibit 1 illustrates. In it, scores are

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Exhibit 1 here

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the same for $Patent_1$ (which has citations from nine different technology classes) and for $Patent_2$ (which has citations from four different technology classes). A patent whose citations were all from a single technological subcategory would have a score of zero. Their scoring methodology cannot accurately address the nearness of cited scientific technologies to those of the granted patent because of flaws in the USPTO's technological classification scheme which did not recognize emerging technologies effectively.

Instead of patent counts, distance scores could be used to estimate the breadth of a patent's technological roots by comparing the patent's assigned technology class codes with those of the antecedents cited in a patent's application to ascertain differences in technological class codes. Like the Hall, *et al* (2001) score, the interpretation of a distance score would be that if all of the cited patents are in the same technology class as the patent in question, the patent's backward dispersion score would be low – indicating that the patent had not synthesized very diverse technological roots. Conversely if the pre-existing patents cited in a patent's application were from highly-diverse technology classes that were different from the core codes of the granted patent, the patent's backward dispersion score would be high[2] because it had synthesized ideas that seem to be unrelated or improbable of appearing together – unless those combinations of technology class codes did, in fact, frequently appear together in other granted patents or the firm's patent mirrored similar patterns of relatedness in its technology class codes.

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[2] A high dispersion score suggests that a patent is far out of the innovators' technological "comfort zone" and may suggest that exposure to highly-diverse intellectual stimuli occurred when the firm's innovators were synthesizing ideas about commercializable inventions.

In distance scores, the breadth of a patent's synthesis of technological roots can be characterized by using measures of technological nearness of the technology class codes being cited. The "nearness" of certain technology class codes to each other is critical in distance score methodology to gauging how far-reaching a firm's patent may be in its innovative content -- as is the detection of those gestalts of technology class codes that are cited together more frequently by patent examiners than are other combinations (Benner and Waldfogel, 2008). Because the USPTO classification system reflects an old-economy bias whereby technological categories were added incrementally over time without any provisions made in the numbering system for technological similarities, we used the *Derwent World Patents Index Classification Guide* (Thomson Reuters, 2013) [3] which categorized each patent according to a consistent classification system of related technology classes[4] and took into account all granted claims of each patent (instead of limiting each patent to a single technology class code as the Hall, *et al* (2001) methodology does). Our distance measures per patent are based on the frequency with which particular dyads of technology class codes appeared together in a particular year.

2.2 Core versus non-core citation counts

For analytical purposes, we assumed that all of the technology class codes assigned to a particular patent application by the Derwent World Patents Index (DWPI) classification system represented that patent's "core" contributions to technological innovation. This is an improvement over methodologies that used only the single, boldfaced USPTO technology class code that appeared on a patent's application to represent the patent's claims because patents

[3] The editorial staff of the *Derwent World Patents Index Classification Guide* indexes each patent into alphanumeric technology categories based on its proprietary classification system which contains subdivisions related to chemical, electrical and mechanical engineering technologies. The Derwent technology classes are more parsimonious than the International Patent Classification (IPC) codes are because a Derwent technology subclass may span several diverse IPCs. The United States Patent and Trademark Office uses the DWPI database heavily in patent examiners' searches of patent applications' antecedents – but not its classification schema.

[4] There are twenty technology sections in the Derwent system for technology classification with as many as ninety classes within a particular technology section. For further granularity, the scientific and engineering staff of the *Derwent World Patents Index* assigned additional four-digit manual codes that are subdivisions of the 289 technology class codes that are used in this study.

awarded to firms like Qualcomm may be granted claims in as many as eighteen (or more) patent technology class codes that we would treat as core technology (*see, for example,* US8159428-B2); some patent applications cite hundreds of cross reference classification codes.

Exhibit 2 provides the mathematical notation for constructing the innovation scores described herein and those variables names are referred to in our exposition of backward-dispersion score construction. Core counts (f_k for i_n) were obtained for each patent by summing

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Exhibit 2 here

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the frequencies of backward-citations having technology class codes in common with those granted to the patent. Each core count f_k was weighted by averaged probabilities a_i reflecting the annual occurrence of particular dyads of technology class codes (among all patents that were granted in that particular year -- which was defined as the application year of the patent under analysis) and when the process was replicated for additional patents, the weighting factors p_j for each particular dyad were adjusted for each patent's respective application year to reflect technological convergence which was occurring across all patents granted in that respective year.[5]

Non-core counts (f_k for o_m) were obtained for each patent by summing the frequencies of backward-citations having technology class codes that were different from the patent's core codes. The non-core counts f_k were each also weighted by averaged probabilities a_o reflecting the annual occurrence of particular dyads of technology class codes (in which each of the patent's core codes i_n was a member of one of the set of dyads being considered for a particular non-core class code o_m). The dynamics of technological convergence were reflected by adjusting the dyads' weightings p_j for each particular dyad on a year by year basis to reflect combina-

[5] Because technology was evolving over time, the interaction probabilities between technology class codes changed from year to year. Weightings were computed by year to capture these differences in technological convergence and were always based on dyads that included at least one core technology class code in the pairings.

tions of technology streams that were becoming increasingly commonplace in citations of subsequent patents which built upon them.

2.3. Dyad weightings, frequency factors and adjustment factors

2.3.1. Frequency factors: Each patent was coded with one or more Derwent technology class codes which represented its core i_n and non-core o_m technological antecedents (if any). A count of the number of times that a particular technology class code appeared in backward-cited patents was used to calculate a *frequency factor* ff_k (which is a percentage of the total number of times core i_n and non-core o_m technology class codes appeared in the list of patents cited by the patent examiner). Dyad weightings a_i,a_o were multiplied by the frequency factors ff_k to provide each technology class code's weighted score W_k.

2.3.2. Dyad weightings: Technological nearness was calculated as the distance from a patent's core technology and was indicated by the weightings a_i,a_o provided by averaging the probabilities p_j of particular technology class codes appearing together on all patents granted in a particular year. Where any patent's backward citations fell into more than one technology section -- whether the class codes were in different parts of a technology family, *e.g., W06* [aviation, marine and radar systems] and *W05* [alarms, signaling, telemetry and tele control], which are in the same technology section (communications) or in entirely different technology sections, *e.g.,* communications [*W*] versus computing [*T*] -- the Derwent classification scheme listed the patent under each of the appropriate Derwent technology class codes (and two-way probability weights p_j were computed for their joint citations in the matrix that was used to build the patent's backward dispersion measure). [6] The dyad weighting a_i,a_o for each respective row representing a core i_n (or non-core o_m) technology class code was the average of all of its dyad weightings for interactions with itself and all other core technology class codes.

[6] Two-way probabilities means that in the joint probability matrix used for calculating dyad weights p_j, each member of the dyad was treated as denominator for its respective cell of the matrix. For example, if the dyad's members are W01 and T01, their joint probabilities p_j would be reported in the matrix both as a proportion of all appearances of W01 and elsewhere also as a proportion of all appearances of T01. The joint probability of W01 appearing with itself was 100 percent (as it was for the probability of T01 appearing with itself); joint probabilities equaling 100 percent formed the diagonals of the joint probability matrix.

Technology evolved such that the class codes from certain Derwent technology sections appeared together more frequently than they appeared with adjacent class codes in the same technology family. For example, if a patent application were filed in 2001, the probability p_j of the technology class code dyad *T01* [for digital computers] and *W01* [telephone and data transmission systems] occurring was 14.1 percent, while the probability p_j of *T01* appearing with *T02* [for analog or hybrid computers] was 0.2 percent for that same year. In our weighting scheme, the dyad of *T01* and *W01* would be weighted more heavily than the dyad of *T01* and *T02,* if they occurred in a patent's backward citations.

2.3.3. Weighted scores: The frequency factor ff_k for each technology class code count was multiplied by its *average dyad weighting* a_i,a_o. Because a patent application typically had multiple Derwent technology class codes, the probability values p_j used as dyad weightings for each of the patent's respective technology class codes were averaged (by the patent's number of core codes) across rows of the joint probability matrix to calculate an average dyad weighting a_i,a_o. The frequency factor of each respective Derwent technology class code was multiplied by its average dyad weighting to create *weighted scores* W_k (which were multiplied by a factor of 100 for scaling purposes).

Summing the weighted scores W_k (the product of *frequency factors* ff_k multiplied by *average dyad weightings* a_i,a_o) produced the patent's Raw Innovation Score, R. As with the Trajtenberg, *et al* (1997) and Hall, *et al* (2001) measures, a low backward R-score indicated that the dispersion of citing patents' technology class codes was actually close to those of the patent's core technology class codes. A high backward R-score indicated that the dispersion of citing patents' technology class codes were indeed substantially different from those of the patent's core technology class codes. The weighted scores W_k obtained from each row of the joint probability matrix reflected technological basicness which was its closeness to the evolving state of science.

2.3.4. V-Score adjustment: The R-score alone *could* indicate a patent's backward dispersion score, but a further adjustment was added to weight more heavily the effect of having mostly non-core patent citations (or mostly core patent citations). The adjustment was that the proportion obtained by dividing the count of non-core citations Σf_o by the count of core citations Σf_i was then multiplied times the R-score to produce the V-score. Because the V-score adjustment was high where most patents cited pre-existing patents having technological class codes that were different from their core technology class codes (and low where most backward-cited precedents had the same technology class codes as the patent's core class codes), resulting V-scores accentuated the extremes of narrow dispersion from a patent's core codes as well as the high dispersion which we interpreted as evidence of out-of-the-box syntheses of technological streams.

Each of the V-score components – core scores and non-core scores (which are combined to create raw scores or R-scores) as well as the proportion of non-core to core scores – could be used to test relationships between the intellectual antecedents of firms' patents and financial performance. Because the V-score was constructed to amplify the effects of very narrow ranges as well as broadly diverse ranges of cited technology class codes, we expected V-scores to possess greater predictive power.

In summary, we proposed using distance-score methodology to create backward dispersion scores which were indicators of how broadly a patent had incorporated inventions from diverse technological streams. By distinguishing between those technology class codes that were already included among the patent's granted codes (which represented its core technology i_n) -- versus those codes that were different, hence non-core o_m -- we constructed a scoring methodology that counted the frequency f_k with which every core and non-core technology class code appeared in the patents cited by the patent examiner. We weighted each count by the average probability a_i,a_o with which each technology class code dyad appeared together in patents granted in a particular year. Finally we modified the resulting summed R-score (or *Raw Innovation Score*) by a ratio Σf_o / Σf_i that captured the proportion of non-core to core technology class codes appearing in the patent's backward citations to create the V-score. We expected that both forms of backward dispersion score, the R- and V-scores, could provide insights concerning a firm's financial performance when such scores were averaged for a year-by-year (or longer) period of aggregation and we used the patterns of resulting, aggregated backward dispersion scores to illustrate those benefits using simple regressions.

3. Use of dispersion scores as predictors of firm performance

Hall, *et al* (2001) scores, R-scores and V-scores were calculated for all patents granted to thirty-two firms who made acquisitions in the communications services industry between 1998 and 2005.[7] Backward patent citation information was provided by Thomson Reuters (Scientific) and averaged year-by-year backward-dispersion scores were calculated using each firm's patents within the window of 1994 through 2012. The patent scores were matched with year-by-year performance data to facilitate time-series analysis of the relationship of each firm's yearly R- and V-scores on performance. Briefly, high yearly V-scores indicated years when a firm's patent applications cited more non-core technology class codes (indicating the use of more out-of-the-box knowledge) than core technology class codes (indicating patents building on incremental knowledge). Year-by-year V-score averages were expected to capture finer-grained differences in the antecedents of firms' patenting activity than did three-year, four-year or seven-year averages that have been used to examine effects on performance (Ernst, *et al*, 2011; Gomes-Casseres, *et al*, 2006; Hitt, *et al*, 1991; Sampson, 2007; Schilling and Phelps, 2007).

Because technologies evolved rapidly during those years -- as it became possible to digitize and transmit voice, data and video over one network -- many diversified firms entered the communications services industry through acquisitions to supplement their internal technology gaps. Their post-acquisition, financial-performance patterns were examined using the Hall, *et al*

[7] The acquiring firms were 8x8 Inc., Alere, Ameritech, Armstrong World Industries, AT&T, Avaya, BellSouth, Comcast, Cypress Semiconductor, Deutsche Telecom, Direct TV, (L.M.) Ericsson, General Dynamics, General Electric, J2 Communications, Level 3 Communications, Lucent Technologies, NCR, Nippon Tel & Tel, NTS, PC-Tel, Polycom, Qualcomm, Qwest, Raytheon, Research in Motion, Sony, Sprint, Teliasonera, Time Warner, Verizon and Western Wireless.

(2001) counting methodology (illustrated in Exhibit 1) and the distance-score methodology that produced R-scores and V-scores (described in Exhibit 2). The post-acquisition backward dispersion scores were used as predictors of firms' return on assets, return on sales and Tobin's q values (as well firms' costs per patent).

3.1. Methodology

3.1.1. Data sources: Financial information was taken from COMPUSTAT (2013) and patent citation information was taken from the Derwent World Patents Index (2013) which used a parsimonious classification system of 291 technology class codes that categorized patent documents for all technologies. Lists of patents to parse for backward citations were taken from Web of Science (2013); Thomson Reuters (Scientific) data provided USPTO, IPC, CPC and Derwent technology class code systems of classification. The replication of the Hall, et al (2001) methodology used patents' USPTO technology class codes -- which were categorized according to their 36-category classification system. The R- and V-score measures used the DWPI classification system to provide their technology class codes.

3.1.2. Financial performance measures: Because inventions were expensive to patent and required time for their impact to become recognized, a lag was anticipated between receiving patents and enjoying their benefits (Gurmu and Pérez-Sebastián, 2008; Hall, *et al,* 1986; Hausman, *et al,* 1984). We assumed that a one-year lag would transpire before profitability -- represented by operating margins (ROS) and return on assets (ROA) -- would show the effects of years with many out-of-the-box inventions and that a three-year lag would transpire before seeing any impact from such patents on the Tobin's q measure. Briefly, we expected that possession of out-of-the-box patents would increase a firm's return on total assets (ROA) and that investors would eventually acknowledge possession of such valuable patents in firms' stock prices (which, in turn, were expected to reflect investors' expectations regarding the future cash flows that would be generated by exploiting the potential knowledge synthesis represented by out-of-the-box patents).

Following Gompers, Ishii, Metrick (2003), Tobin's q was calculated as the market value of assets divided by the book value of assets, where the market value of assets was computed as 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. An interesting feature of the data series examined was that during the stock market run-up which 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. It is possible that Internet economics exerted pressures on market valuation that were contrary to those which were anticipated in our tests.

4. Results

4.1. Return on Assets: R-scores were tested to contrast the efficacy of the two methodologies for predicting return on assets (ROA) for Time Warner and Comcast in Exhibit 3. First,

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the yearly backward dispersion scores from the distance-score and Hall, et al (2001) calculations are shown. Each series was created by averaging all scores of patents' backward citations that were calculated for each particular year. In Exhibit 3, results from using the two methodologies are graphed on the same axes to illustrate that the R-score values calculated using the distance-score methodology were similar to the scores computed using the Hall, *et al* (2001) methodology for Time Warner – but less so in the early years of the series. Time Warner was a highly-diversified competitor, but the Hall, *et al* (2001) methodology for calculating backward dispersion scores suggested that Time Warner's patents built upon a more diverse variety of technological class codes before 2001 than the R-scores indicated. By contrast the R-score methodology indicated that the range of different technological class codes built upon over time by Time Warner's patents became narrower as the thrust of Time Warner's diversification grew more closely-related, its innovation path grew more incremental, and divestitures were made.

The patterns of Comcast's two series of backward dispersion scores were also quite similar in Exhibit 3 for the two methods of computing them -- until after 2006. The yearly R-scores built using the distance-score methodology suggested that, after 2006, Comcast's inventions were subsequently built upon a broader range of technology class codes than the Hall, *et al* (2001) scores suggested. The R-scores better reflect the diversity of technologies that Comcast synthesized after it entered the software business and also acquired MGM (and United Artists).

Exhibit 3 also matched the backward dispersion scores from the two computational methods with the firms' financial measures of return on assets (ROA) one year thereafter. When the two sets of Time Warner's backward dispersion scores were matched with its lagged measures of return on assets, the patterns for both series of dispersion scores were significant predictors of Time Warner's ROA -- except that the sign of the Hall, *et al* (2001) series was negative (which was a reflection of the wider backward dispersion scores that their methodology produced for the period before 2001).

For the prediction of Comcast's return on assets, Exhibit 3 shows that only the R-scores were significant (and not the Hall, *et al* (2001) scores). Comcast's return on assets fluctuated widely during the period of 1998 through 2012 and the backward dispersion scores calculated using the distance-score methodology were better predictors of Comcast's fluctuating financial performance than was the Hall, *et al* (2001) methodology (which was not significant with any performance lag tested for Comcast specifications).

The R- and V-scores were similar for the patents of Time Warner and Comcast. Slopes created by both scores were positive when predicting ROA. Because the adjustment factor of the V-score amplified the extremes of backward-citation patterns – which could include having few rather than many non-core technology class codes – the amplified V-scores were used to predict firms' return on sales (ROS), Tobin's q values and costs per patent in subsequent tests. (Backward dispersion V-scores and ROA performance data were also pooled for the time series of the thirty-two firms in the sample. A positive and significant relationship between them was obtained for the pooled time series when a two-year lag with ROA was specified.)

4.2. Return on Sales: For Exhibit 4 -- which compared the two series of backward dispersion scores using the patents of Lucent Technologies and Level 3 Communications – V-scores

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Exhibit 4 here

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were contrasted with Hall, *et al* (2001) scores. Return on sales was calculated on operating revenues – before debt-servicing costs and before depreciation (which evidenced high capital investments). Results indicated that the patterns representing backward citations for Lucent Technologies' patents were similar for the V-scores and Hall, *et al* (2001) methodology -- until Lucent Technologies merged with Alcatel in 2006; the V-scores for citations on patents received from 2006 through 2011 indicated that, on average, Alcatel-Lucent's patents cited a broader range of technological class codes in its inventions during that period than the Hall, *et al* (2001) scores suggested -- with 2011 being its year of most-radical backward dispersion scores.

Fluctuations which were captured by using the V-scores were especially dramatic in the example of Level 3 Communications which was spun off from Peter Kiewit & Sons as a start-up in 1998 and developed gateway VoIP technologies. The V-score methodology captured Level 3 Communications' wide annual fluctuations in backward dispersion scores which occurred as its patents synthesized the diverse inventions needed to assemble a system of end-to-end, B2B communications services (including video over internet protocol for on-demand content -- services like *Netflix*) – a pattern which the Hall, *et al* (2001) scores did not reflect.

As Exhibit 4 indicates, both sets of dispersion scores were significant as predictors of Lucent Technologies' return on sales, but the coefficient of the V-scores showed greater statistical significance in the example of Lucent Technologies because its weighting emphasized the effect of the firm's non-core patent citations. The *V*-scores were also significant predictors of Level 3 Communications' return on sales because they depicted the firm's wide yearly swings in the breadth of non-core technology antecedents cited in its patents. The pattern of backward patent scores obtained using the Hall, *et al* (2001) methodology was not significant in predicting variations in the return on sales for Level 3 Communications – except when specifying a three-year lag -- which lacked theoretical validity since ROS is a short-term performance measure. (Backward dispersion *V*-scores and ROS performance data were pooled for the time series of the thirty-two firms in the sample. A positive and significant relationship between them was obtained when a one-year and two-year lag with ROS was specified; the patent score's coefficient was more significant for the one-year lagged specification and the corrected R^2 was higher for the one-year lagged specification.)

4.3. Tobin's q: Predictions of Tobin's q assumed that a three-year lag existed in any relationship between a firm's patents' backward dispersion scores and the market's reaction to patents granted. Exhibit 5, which compares the relationship between dispersion scores built from patents' backward citations and Tobin's q for General Electric and Qualcomm, shows that both

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Exhibit 5 here

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dispersion-score calculation methodologies were effective predictors of Tobin's q values but that backward dispersion scores were typically negatively-correlated with Tobin's q – perhaps because investors were skeptical about the efficacy of out-of-the-box inventions and risk-averse concerning their virtues until commercial success was evident. Similar results were obtained when one- and two-year lags were specified for testing the relationship between GE's and Qualcomm's patents' backward dispersion scores and the market's response (as proxied by Tobin's q values); the relationships were always negative and statistically-significant in all specifications tested.

To examine further the relationship between backward dispersion measures and Tobin's q, we analyzed the patent citations of L.M. Ericsson and AT&T (as well as those of the other firms in the study). Results were consistent with the observed negative patterns between backward dispersion scores and Tobin's q with a three-year lag. The Tobin's q patterns were negative and statistically-significant for 74.3 percent of the tests specified when using the V-scores; they were negative and statistically-significant for 76.9 percent of the relationships examined when using the Hall, *et al* (2001) computation method. Exhibit 6 shows the relationship

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Exhibit 6 here

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between Tobin's q and backward dispersion scores for AT&T and L.M. Ericsson. The V-score for AT&T was negative (but not significant). The Hall, *et al* (2001) scores for L.M. Ericsson were positive (but not significant). Ironically both methodologies produced backward dispersion scores that increased over time while AT&T's valuation fell during the years when it waivered on the edge of bankruptcy and was subsequently acquired by SBC Corporation. Indeed, the V-score methodology calculated that the highest backward dispersion scores were found in the group of patents that were granted three years before the market's lowest valuations of AT&T.

No specifications were significant when relationships between Tobin's q values and backward patent V-scores for the time-series of the thirty-two sample firms were pooled – regardless of the length of lag that was specified. Negative (but not significant) coefficients were obtained for all patterns of backward dispersion V-scores which were tested using the pooled time series.

Field interviews suggested that the negative relationship between backward dispersion scores and Tobin's q measures may have occurred due to the stock market meltdown after the bursting of the Internet bubble. Those communications services firms without fundamental patent families to generate revenues between 2000 and 2004 typically filed for bankruptcy and/ or were acquired during this period. Patents are presumed to be valuable (Belenzon, 2011;

Cockburn & Griliches, 1988; Cockburn, *et al*, 2000; Griliches, 1981; Trajtenberg, 1990; Trajtenberg, *et al*, 1997), so the negative pattern of Tobin's q for evidence of the fruits of exploratory innovation was puzzling but consistent with findings by Sears and Hoetker (2014).

4.4. Cost per patent. Appendix I shows the relationship between backward dispersion scores and the cost per patent (in millions) for four firms who made acquisitions in the communications services industry between 1998 and 2005.[8] Annual research and development expenditures were divided by their annual number of patents awarded to calculate their respective average costs. Tests used varying lags and results illustrate that those patents which were, on average, synthesized from the most-diverse technological streams were the most-expensive patents to produce. This positive pattern was found for fourteen of eighteen firms which were individually tested. In these tests, most-recent years (e.g., 2011 or 2012) were dropped from specifications because of the lag between when patent applications were made and when patents were subsequently awarded. Their inclusion skewed results because most-recent R&D expenditures are divided by fewer granted patents (because many applications are presumably pending), which drove up the cost per patent significantly. (Alternatively, the productivity of inventive activity during 2011 and 2012 has fallen dramatically compared with earlier years.) When the time-series of the thirty-two sample firms were pooled, positive and significant relationships were obtained between *V*-scores and annual costs per patent when specifying a three-year lag.

5. Discussion and conclusions

The *V*-scores amplified the highs and lows in the breadth of non-core technology class codes reflected in patents' backward citations and captured greater fluctuations in the evidence of building on out-of-the-box technological streams. Both *V*- and *R*-scores were more sensitive to fluctuations in firms' financial performance than were the Hall, *et al* (2001) scores.

[8] 8x8 Inc., Avaya, (L.M.) Ericsson, General Electric, Lucent Technologies, Polycom, Qualcomm, Raytheon, Research in Motion, and Sony showed a positive and statistically-significant relationship between backward dispersion scores and cost per patent when the *V*-score was tested.

We concluded that the R-scores (and their components) were better predictors of return on assets and reflected patterns of higher backward dispersion than the Hall, *et al* (2001) scores did -- even where the number of different technology class codes decreased (if those backward cited patents happened to be from technologies that were different from the patent's assigned technology codes). Coefficient signs were in the same direction for all tests of financial measures using V- and R-scores.[9]

The Hall, *et al* (2001) scores deviated less from year to year than did the V- and R-scores (perhaps because they lacked the weighting differences that reflected the changing likelihoods of some technological class codes occurring together over time due to technological convergence). Hall, *et al* (2001) coefficient signs were most similar to the V- and R-scores for the Tobin's q specifications. All tests using the V- and R-scores showed that a negative relationship existed with Tobin's q -- regardless of the length of lag assumed – but the Hall, *et al* (2001) scores indicated a positive relationship with Tobin's q for 30 percent of the firms analyzed[10] and those positive results persisted, regardless of the length of lag tested.

The signs of the Hall, *et al* (2001) coefficients differed from those of the V- and R-scores for three of the ten firms when testing return on sales, and for five of the ten firms when testing relationships with return on assets. Additional testing is needed to ascertain which directionality is supported by theory, especially for understanding the relationship of backward dispersion scores with respect to return on assets, which was the performance measure where contradictory signs were most frequently found when comparing the two scoring methodologies.

Results suggest that evidence of out-of-the-box inventions was positively correlated with high returns on assets and sales, but not with Tobin's q. It appears that synthesizing inventions from diverse technological classes rewarded the innovating firms, but that those rewards

[9] In addition to augmenting an R-score to make a V-score, it is possible to decompose the R-score into a C-score (for core-only components) and N-score (for non-core-only components), but analysis of the incremental effects of these components on firms' performance is beyond the scope of this paper.
[10] The Hall, et al (2001) scores indicated a weak positive relationship with Tobin's q for L.M. Ericsson, Comcast and Direct TV.

were not necessarily reaped by the owners of those firms who grew through acquisition. The market (represented by Tobin's q) seemed slow to recognize any positive effects from building on highly-diverse precedents and did not seem to value the out-of-the-box inventions that we associated with the high backward-dispersion scores. More study is needed regarding how firms benefit from building on extant patents that represent ideas from significant non-core technology classes. Analysis of forward-dispersion scores using a similar, distance-score methodology is also indicated.

The Hall, et al (2001) measures of patent originality rely upon the same older USPTO technological classes used by Trajtenberg (1990), Hall and Ziedonis, (2001), Argyres and Silverman (2004), Banerjee and Cole (2010), Novelli (2011), Valentini and DiGuardo (2012) and Miller, et al (2014), among others. That classification system lacks the granularity needed to describe important nuances in citation patterns for the newer technological streams and their weighting methodology fails to suggest the nearness of technological class codes that were built upon by subsequent patents. It would be possible to compute yearly dyad scores for the 96 categories of Hall, et al (2001)'s NBER database for each the available years to apply the weighting system that we suggest (which was up to 2006 at this time). Similarly, it would be possible to apply the weighting system that we suggest to the USPTO system of technology class codes – if dyad scores detailing the joint probabilities of each pair of class codes occurring in each year could be calculated.

The distance-score methodology provided a superior basis for weighting the distribution of backward-cited patents. The R- and V-scores were better-suited to capturing the potential convergence of emerging technologies because their weighting system was a reflection of the evolving frequency with which particular technological class codes appeared over time. The classification scheme of the Derwent World Patent Index facilitated a finer-grained analysis of how technological streams were synthesized by inventors than had previously been employed in studies of technology strategy. Calculation of a patent's R-score (V-score enhancement), C-score and N-score provides a viable methodological alternative for tracking changes in the content of firms’ innovation strategies when they enter new markets that have not previously been served or diversify along new avenues of technology.

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7. References

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

Argyres, NS and Silverman, B (2004). R&D, organization structure, and the development of corporate technological knowledge. *Strategic Management Journal*. 25: 929-958.

Banerjee, PM, Cole, BM, 2010. Breadth-of-impact frontier: How firm-level decisions and selection environment dynamics generate boundary-spanning inventions. *Technovation*. 30: 411-419.

Hapuji, H, Loree, D, Crossan, M. 2011. Connecting external knowledge usage and firm performance: An empirical analysis. *Journal of Engineering and Technology Management*. 28: 215-231.

Belenzon, S. 2011. Cumulative innovation and market value: Evidence from patent citations. *Economic Journal*. 122:265-285.

Benner, M, Waldfogel, J. 2008. Close to you? Bias and precision in patent-based measures of technological proximity. *Research Policy*. 37: 1556-1567.

Cockburn, IM, Griliches, Z. 1988. Industry effects and appropriability measures in the stock market's valuation of R&D and patents. *American Economic Review, Papers and Proceedings.* 78: 419-423.

Cockburn, IM, Henderson, RM, Stern, S. 2000. Untangling the sources of competitive advantage. Strategic Management Journal. 21: 1123-1145.

Cohen, WM, Levinthal, DA. 1990. Absorptive capacity: a new perspective on learning and invention. *Administrative Science Quarterly*. 35: 128-152.

COMPUSTAT North America (2013). NY: Standard & Poor's.

Dahlin, KB, Behrens, DM. 2005. When is an invention really radical? Defining and measuring technological radicalness. *Research Policy*. 34: 717-737.

Ernst, H, Lichtenthaler, U, Vogt, C. 2011. The impact of accumulating and reactivating technological experience on R&D alliance performance. *Journal of Management Studies*. 48(6): 1194-1216.

Garcia, R, Calantone, R. 2002. A critical look at technological innovation typology and innovativeness termi-nology: a literature review. *Journal of Product Innovation Management*. 19(2): 110-132.

Gomes-Casseres, B, Hagedoorn, J, Jaffe, A. 2006. Do alliances promote knowledge flows? *Journal of Financial Economics*. 80: 5-33.

Gompers, P, Ishii, J; Metrick, A (2003). Corporate governance and equity prices. *Quarterly Journal of Economics* 118 (1): 107-155.

Green, SG, Gavin, MB, Aiman-Smith, L. 1995. Assessing a multidimensional measure of radical technological innovation. *IEEE Transactions on Engineering Management*. 42(3): 203-214.

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

Gurmu, S, Pérez-Sebastián. 2008. Patents, R&D and lag effects: evidence from flexible methods for count panel data on manufacturing firms. *Empirical Economics*. 35: 507-526.

Hall, BH, Griliches, Z, Hausman, JA. 1986. Patents and R&D: is there a lag. *International Economics Review*. 27: 265-283.

Hall, BH Jaffe, AB and Trajtenberg, M (2001). The NBER patent citations data file: Lessons, insights and methodological tools. NBER working paper no. 8498.

Hall, BH and Ziedonis, RH (2001). The patent paradox revisited: An empirical study of patenting in the US semiconductor industry, 1979-95. *RAND Journal of Economics*, 32(1): 101-128.

Hausman, JA, Hall, BH, Griliches, Z. 1984. Econometric models for count data with applications to the patents R and D relationship. *Econometrica*. 52: 909-938.

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.

Herfindahl, OC (1950). Concentration in the U.S. steel industry. Unpublished doctoral dissertation. Columbia University.

Hitt, MA, Hoskisson, RE, Ireland, RD, 1990. Mergers and acquisitions and managerial commitment to innovation in M-form firms. *Strategic Management Journal.* 11: 20-47.

Hitt, MA, Hoskisson, RE, Ireland, RD, and Harrison, JS. 1991. Effects of acquisitions on R&D inputs and outputs. *Academy of Management Journal*, 34: 693–706.

Hirschman, AO (1945). *National Power and the Structure of Foreign Trade*. Berkeley.

Hirschman, AO (1964). The paternity of an index. *American Economic Review,* 54 (5): 761.

Killing, JP. 1983. *Strategies for Joint Venture Success*. Cengage Learning EMEA.

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

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

Leonard-Barton, D. 1992. Core capabilities and core rigidities: a paradox in managing new product development. *Strategic Management Journal*. 13: 111-125.

March, JG. 1991. Exploration and exploitation in organizational learning. Organization Science. 2:71-87.

March, JG, Simon, H. 1958. *Organizations*. Wiley: New York.

Miller, DJ, Seth A, Lan, S. 2014. Innovation synergy in acquisitions: an evaluation of patent and product portfolios. (University of Illinois: unpublished manuscript).
Nelson, RR, Winter, SG. 1982. *An Evolutionary Theory of Economic Change*. Belknap Harvard: Cambridge.

Novelli, E. (2011). As you sow, so shall you reap: General technologies and entry into new product subfields in the face of technological uncertainty. University of Bath, School of Management, working paper.

Rosenbluth, G. (1955). Measures of concentration. Business Concentration and Price Policy. Princeton: NBER: 57-95.

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

Sampson R. 2007. R&D alliances and firm performance: the impact of technological diversity and alliance organization on innovation. *Academy of Management Journal*. 50(2): 364–386

Schilling MA, Phelps C. 2007. Interfirm collaboration networks: the impact of large-scale network structure on firm innovation. *Management Science*. 53: 1113-1126.

Schoenmakers, W, Duysters, G. 2010. The technological origins of radical inventions. *Research Policy*. 39: 1051-1059.

Sears, JB. Hoetker, G. 2014. Technological overlap, technological capabilities, and resource recombination in technological acquisitions. *Strategic Management Journal*. 35(1): 48-67.

Sorensen, JB. Stuart, TE. 2000. Aging, obsolescence and organizational innovation. *Administrative Science Quarterly*. 45: 81-112.

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

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

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

Tushman, ML, Scanlan, TJ. 1981. Boundary spanning individuals -- their role in information-transfer and their antecedents. *Academy of Management Journal*. 24 (2): 289-305.

Valentini, G and DiGuardo, MC. 2012. M&A and the profile of inventive activity. *Strategic Organization*, 10: 384-405.

Web of Science, 2013. Thomson Reuters. Philadelphia.

Exhibit 1

Sample calculations using methodology of Hall, *et al* (2001)

Patent 1 score = 0.7467

$Patent_1$ has fifteen backward citations from nine different technology classes; seven citations are from technology $class_A$ while there is one citation from each of the remaining technology classes. Technology $class_A$ represents 46.67 percent of the total citations while each of the other eight technology classes represents 6.67 percent of the total citations, making their summed total equal 100 percent. The squared value of technology $class_A$ is 21.78 percent while the squared value of each of the other eight technology classes is 0.044 percent, making their summed total equal 25.33 percent. When this total is subtracted from 100 percent, the result is 74.67 percent.

Patent 2 score = 0.7467

$Patent_2$ has fifteen backward citations from four different technology classes; three citations are from technology $class_A$ while there are four citations from each of the remaining technology classes. Technology $class_A$ represents 20 percent of the total citations while each of the other three technology classes represents 26.67 percent of the total citations, making their summed total equal 100 percent. The squared value of technology $class_A$ is 4 percent while the squared value of each of the other three technology classes is 7.11 percent, making their summed total equal 25.33 percent. When this total is subtracted from 100 percent, the result is 74.67 percent.

Patent 1 has 15 citations										
	Technology Class Codes									
	A	B	C	D	E	F	G	H	I	Totals	1-index
Number of citations in different technology class codes	7	1	1	1	1	1	1	1	1	15	
Precent of total citations	0.47	0.07	0.07	0.07	0.07	0.07	0.07	0.07	0.07	1	
Percentage squared	0.218	0.004	0.004	0.004	0.004	0.004	0.004	0.004	0.004	0.253	0.747

Patent 2 has 15 citations											
	Technology Class Codes										
	A	B	C	D	E	F	G	H	I	Totals	1-index
Number of citations in different technology class codes	3	4	4	4	0	0	0	0	0	15	
Precent of total citations	0.20	0.27	0.27	0.27	0.00	0.00	0.00	0.00	0.00	1	
Percentage squared	0.040	0.071	0.071	0.071	0.000	0.000	0.000	0.000	0.000	0.253	0.747

Exhibit 2

Mathematical Notation for Calculating R- and V- Scores for a Patent

i_n = Core technology class codes of backward citations for Patent where the number of core codes = 1, 2, 3, …, n

o_m = Non-core technology class codes of backward citations for Patent where number of non-core codes = 1, 2, 3, …, m

f_k = Frequency with which a core technology class code$_i$ (or non-core technology class code$_o$) occurred in backward citations of Patent, which is the count of each technology class code appearing in its backward citations where k = 1, 2, ..., n, n+1, ... , $n+m$

$F = \Sigma f_k$ = the sum of all technology class codes

$ff_k = f_k / F$ = the frequency factor for one technology class code

Assume an $n \times (n+m)$ matrix for searching probability p_j that dyads occur in technology class codes of backward citations for $i_n \times i_n$, $i_n \times o_m$ and $o_m \times o_m$ where $j = n \times (n+m)$ and p_j is the dyad weighting for a particular core technology class code$_i$ or non-core technology class code$_o$ appearing with itself or another backward-cited technology class code defined as $i_1, \dots, i_n \times i_1, \dots, i_n, o_1, \dots, o_m$

$a_i, a_o = \left[\Sigma p_j / i_n\right]$ = Average dyad weighting for each inside-the-core technology class code $(i_1 + \cdots + i_n)$ and for each outside-the-core technology class code $(o_1 + \cdots + o_m)$, the sum of each row of weightings divided by the number of core technology class codes that there are.

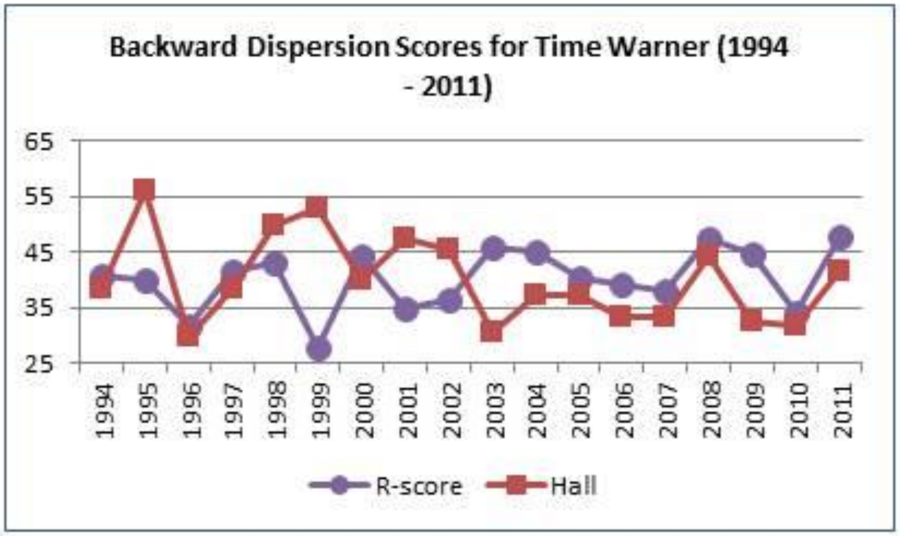
$W_k = a_i{,}a_o \times ff_k$ = the weighted score for a core technology class code$_i$ or for a non-core technology class code$_o$

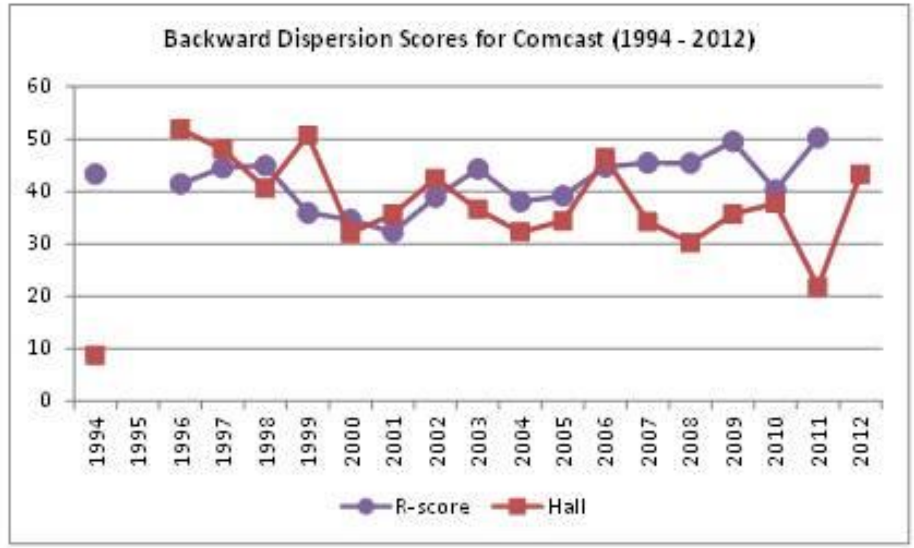
$R = \Sigma W_k$ = Raw Innovation Score, the sum of all weighted scores

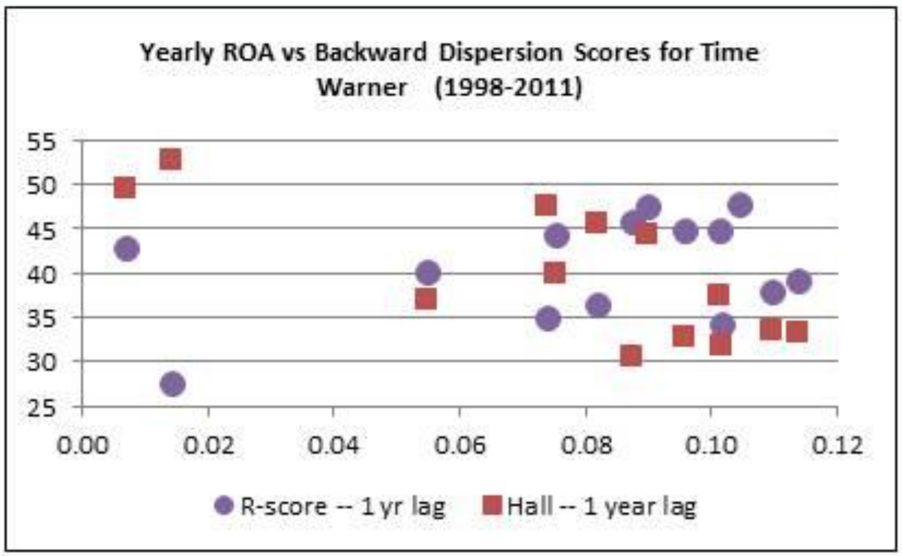
$V = R \times \left[\, \Sigma f_o \,/\, \Sigma f_i \,\right]$ = V- Score, the Raw Innovation Score times the ratio of the count of outside-the-core technology class codes divided by the ratio of the count of inside-the-core technology class codes

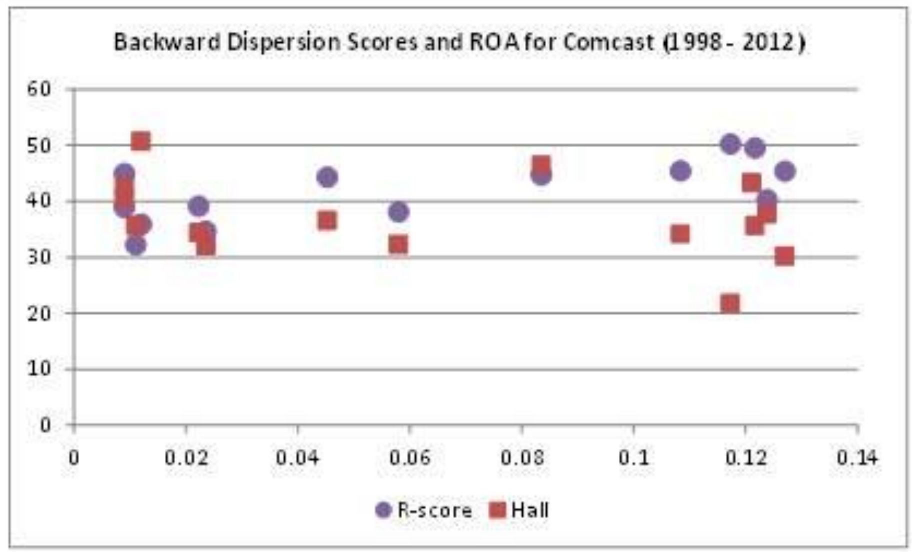
Exhibit 3

Backward Dispersion Scores as Predictors of Return on Assets







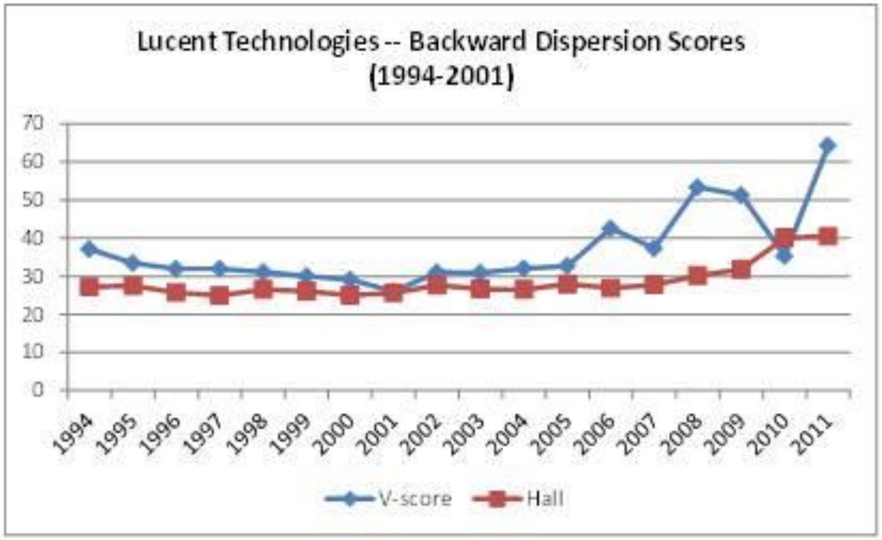


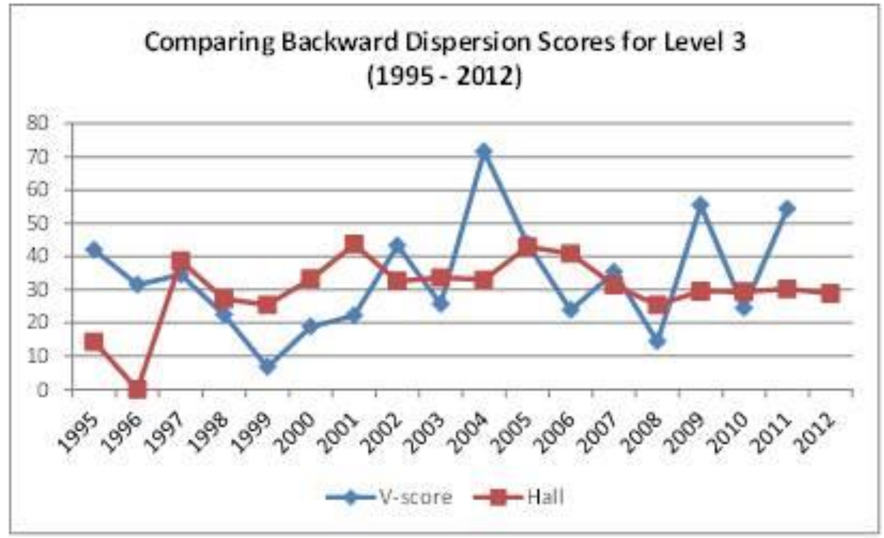
$R^2 = 0.292723$
R-score is positive and significant at 0.0562 level

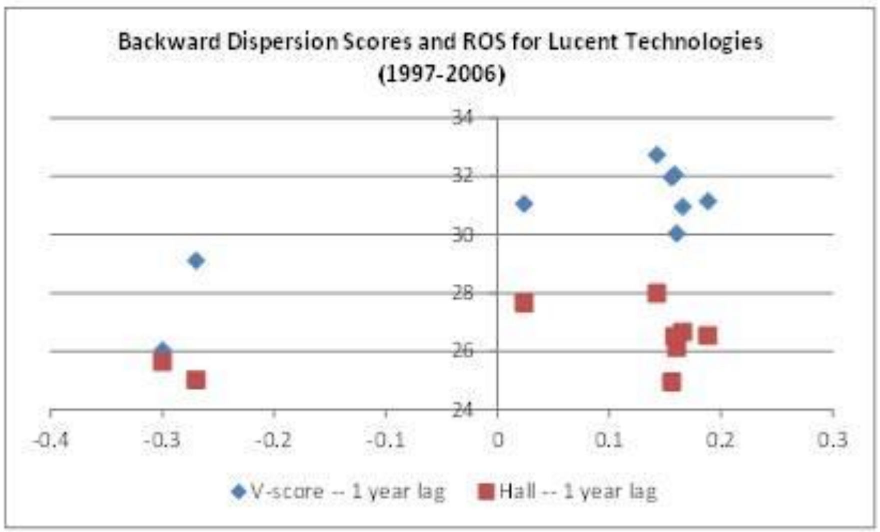
$R^2 = 0.52857$
Hall, et al is negative and significant at 0.0032 level

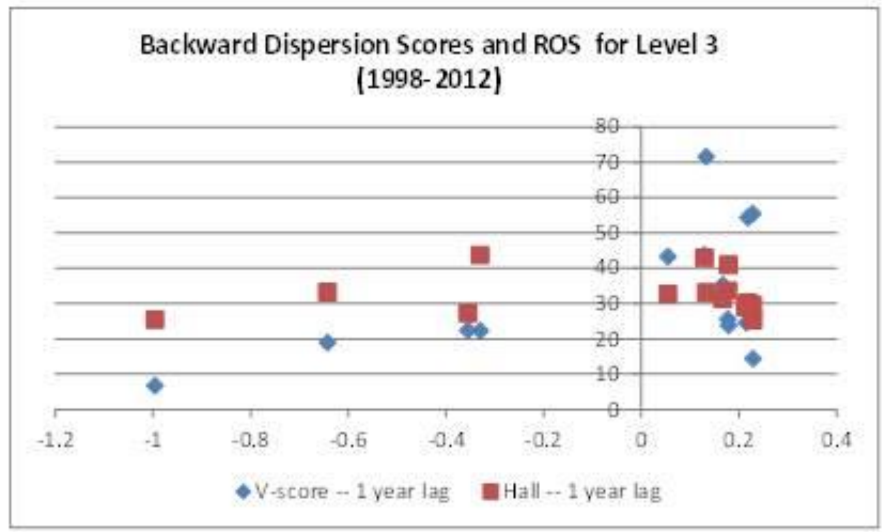
$R^2 = 0.6335$
R-score is positive and significant at 0.0011 level
Hall, et al is not significant

Exhibit 4
Backward Dispersion Scores as Predictors of Return on Sales





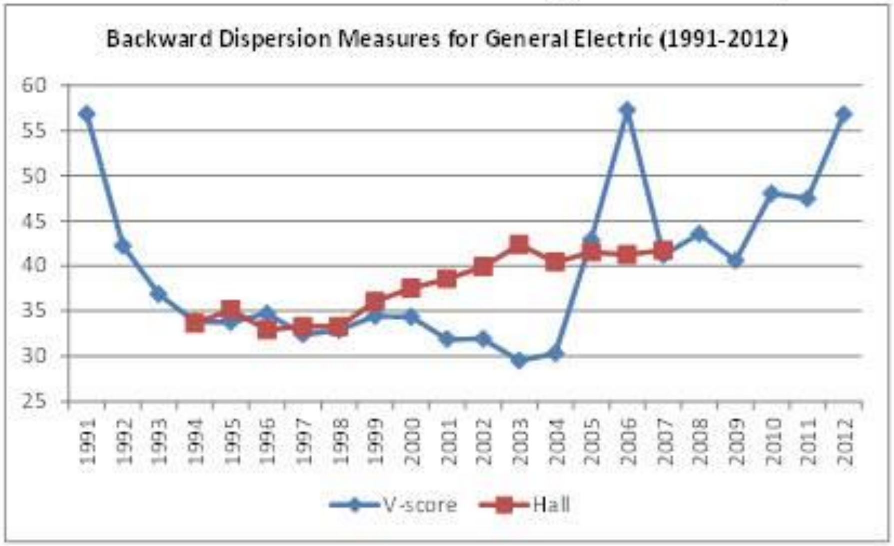


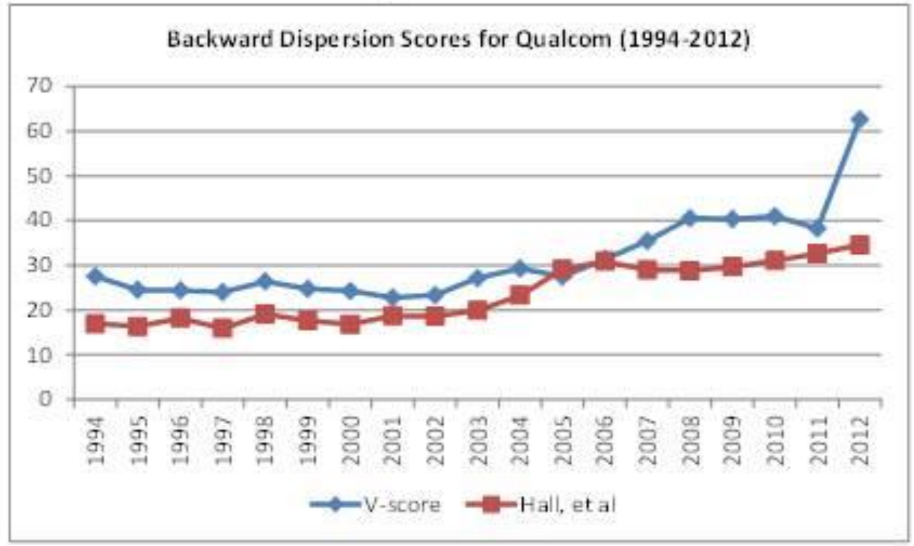


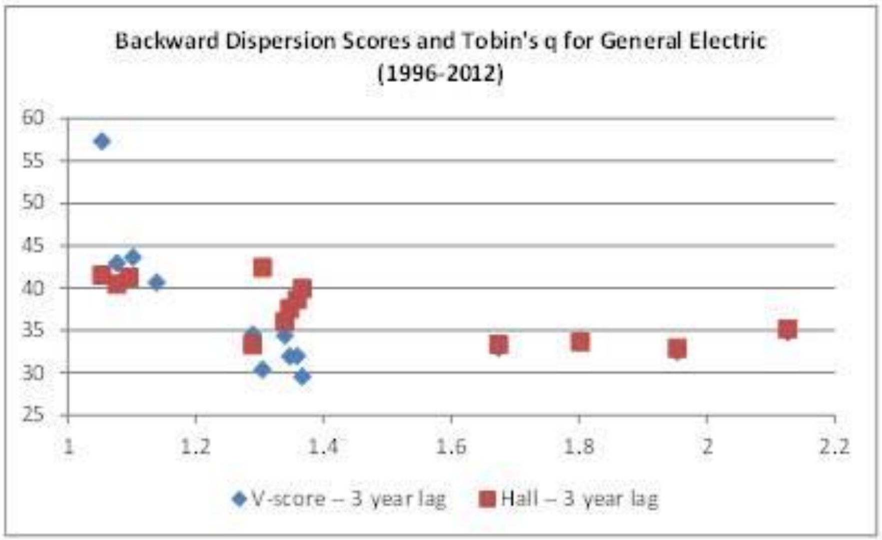
$R^2 = 0.6843$ V-score is significant at 0.0112 level	$R^2 = 0.3934$ Hall, et al is significant at 0.0960 level	R2 = 0.2870 V-score is positive and significant at 0.0592 Hall, et al is not significant

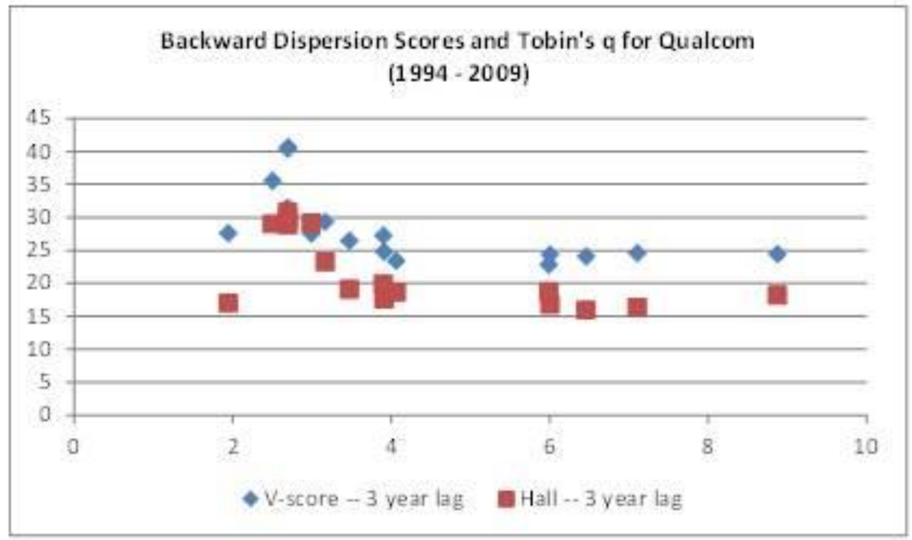
Exhibit 5

Using Backward Dispersion Measures to Predict Tobin's q





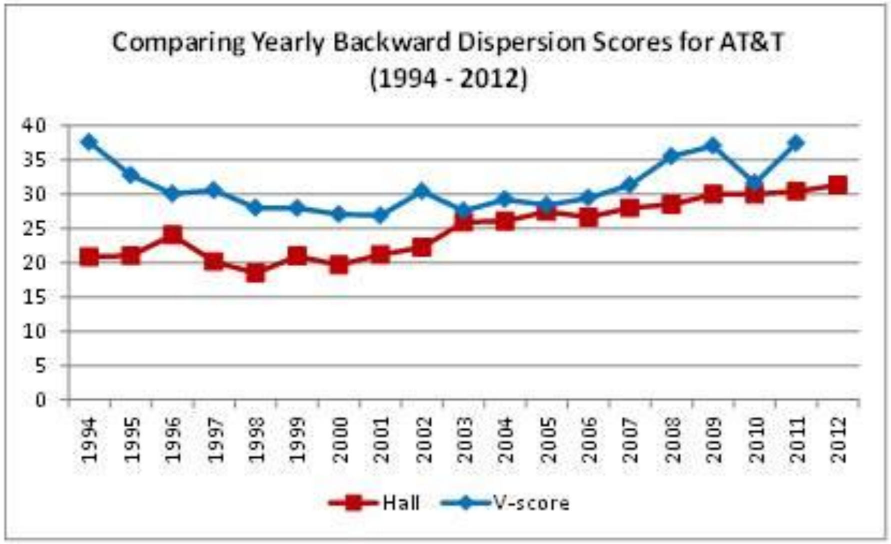


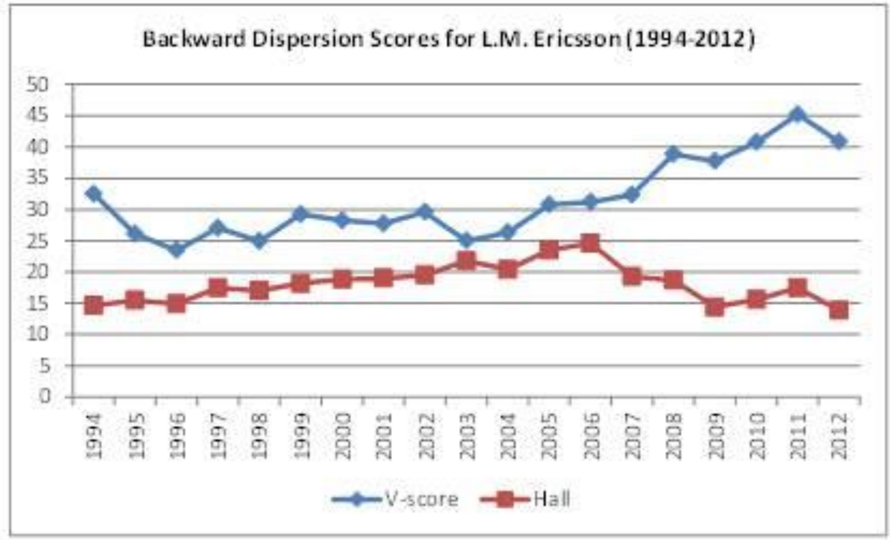


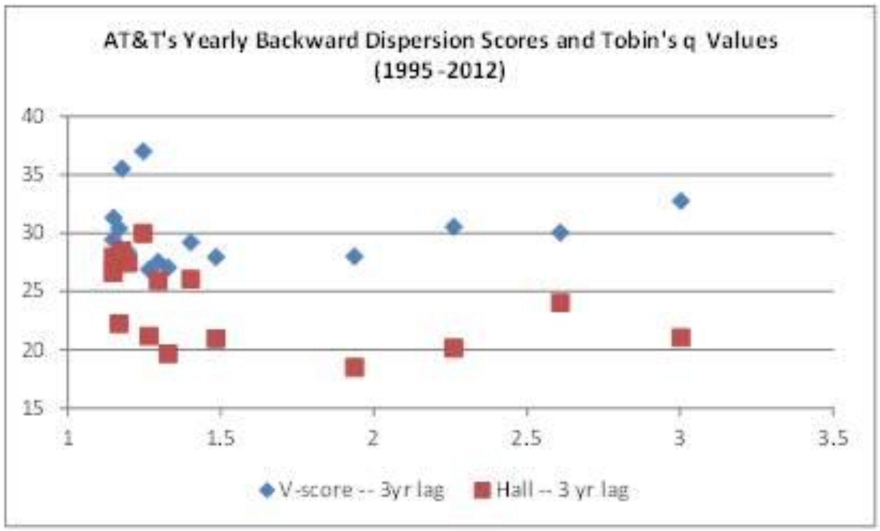
$R^2 = 0.2699$ V-score is negative and significant at 0.0569 level	$R^2 = 0.7266$ Hall, et al is negative and significant at 0.0004 level	$R^2 = 0.4253$ V-score is negative and significant at 0.0084 level	$R^2 = 0.5560$ Hall, et al is negative and significant at 0.0014 level

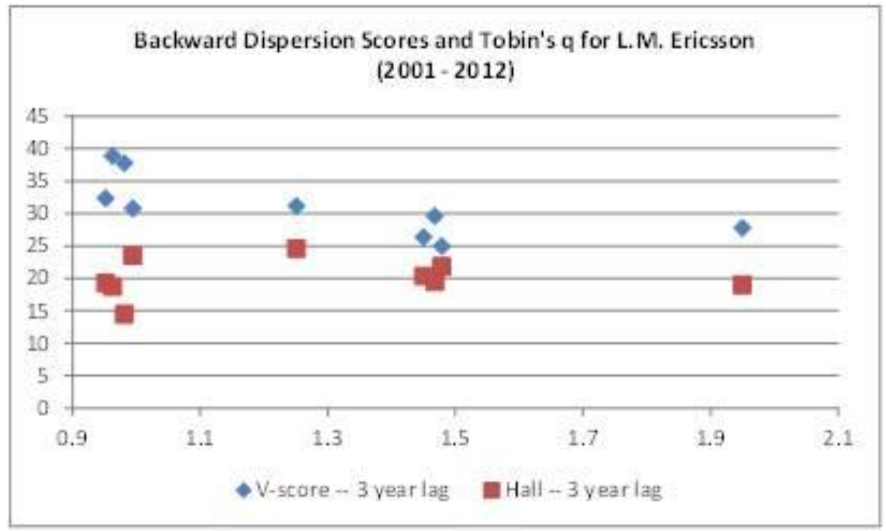
Exhibit 6

Using Additional Backward Dispersion Measures to Predict Tobin's q









R2 = 0.2280

Hall, et al is negative and significant at 0.0718 level

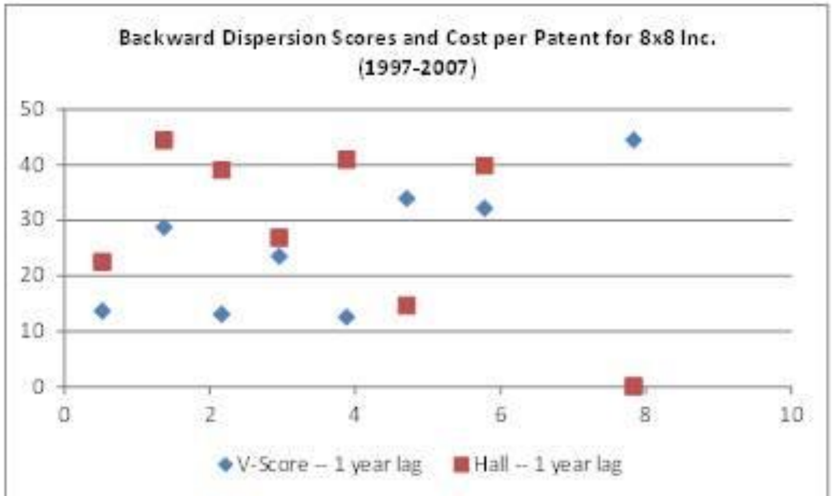
V-score is not significant

$R^2 = 0.6574$

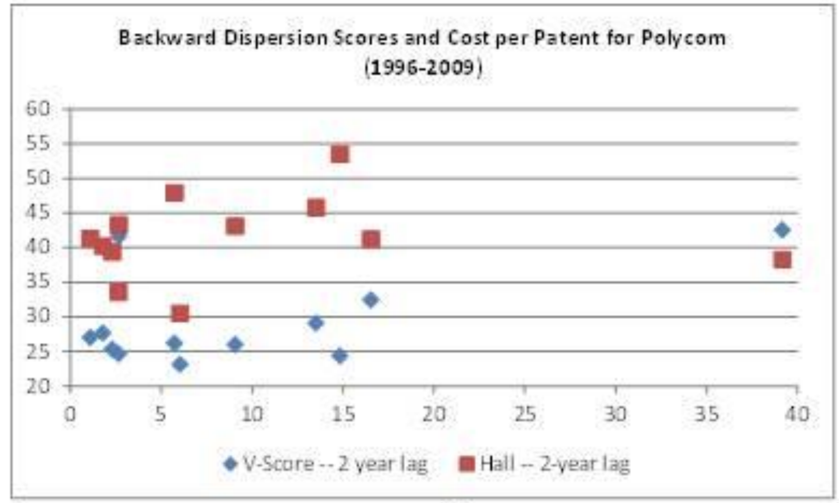
V-score is negative and significant at 0.0146 level

Hall, et al is not significant

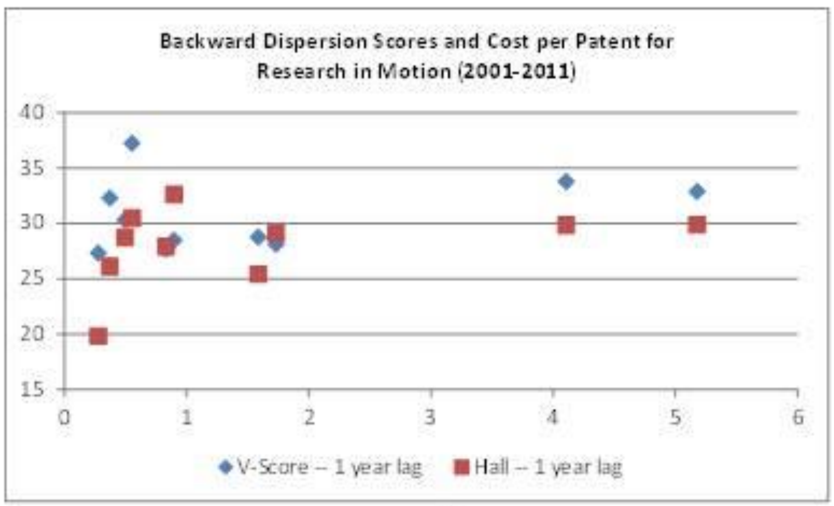
Appendix I
Using Backward Dispersion Scores to Predict Costs per Patent



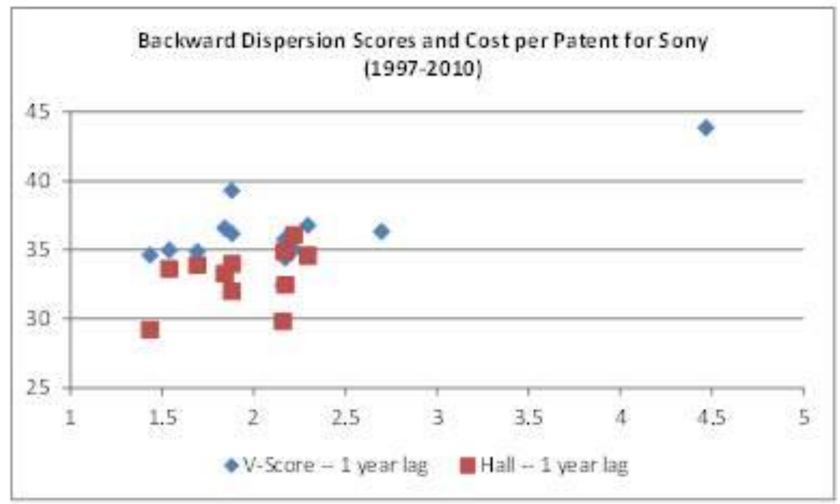
$R^2 = 0.5710$ V-score is positive and significant at 0.0301 level	$R^2 = 0.2791$ Hall, *et al* is negative but not significant



$R^2 = 0.2927$ V-score is positive and significant at 0.0857 level	$R^2 = 0.0085$ Hall, *et al* is positive but not significant



$R^2 = 0.6046$ V-score is positive and significant at 0.0316 level	$R^2 = 0.1127$ Hall, *et al* is positive but not significant



$R^2 = 0.6713$ V-score is positive and significant at 0.0011 level	$R^2 = 0.1602$ Hall, *et al* is positive but not significant