“Empirical Tests for Creative-Destruction in the Pharmaceutical Industry”[1]

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ABSTRACT:

We propose an empirical strategy for estimating competition in innovation markets based on a model of creative-destruction. Our method relates firms’ market equity to information about patent citation patterns. Two innovations we introduce are using daily abnormal stock returns rather than annual measures of Tobin’s *q* and creating citation patterns related to the area of science a firm patents in as represented by the detailed patent classification system. We find that firm’s market value increases when its patent portfolio is cited and when there are citations to an area of science in which they are prominent. Holding this effect constant, we find that citations from the same area of science tend to reduce market value. We interpret these findings as consistent with citations indicating more valuable intellectual property but citations from competing technologies decreasing its value.

Keywords: Patent, Competition, Event Study

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I. Introduction

Market structures in innovative industries often feature firms with considerable market power in product markets. The high prices and profits earned by these firms often draw the attention of policymakers as indicative of a welfare loss from the exercise of monopoly power. This loss is the standard static loss that is often the result of a dynamic process in which firms incur R&D expenses to compete in innovation markets so as to obtain future expected rents. A complete welfare calculation, then, must consider the market characteristics that would have prevailed without the additional R&D costs sunk on the expectation of future rents. An ancillary issue relevant to this calculation is the degree to which the initial innovation markets are themselves competitive. We attempt to uncover evidence of rivalry in the innovation markets from which new products are developed.

Our analyses derive from a form of "Creative-Destruction" (Schumpeter, 1942). Schumpeter posited that continuous innovations resulted in temporary product market monopolies. The monopoly rents earned by an innovator serve to motivate other innovators to develop even more useful inventions. In this way, the product they "create" will "destroy" the market for, and the rents earned by, the previous incumbent. A feature of this model is a continuous stream of new inventions that dominate a market for a while but are eventually replaced by subsequent inventions. More macroeconomic investigations of the creative-destruction hypothesis have explored the rates of creation and destruction over the business cycle (Caballero and Hammour, 1994) and the timing, pace, and efficiency of ongoing job reallocation (Caballero and Hammour, 1996). Plant productivity growth and firm level analyses based on a creative-destruction model are discussed in Foster, Haltiwanger and Krizan (2000). Different firms in different settings choose different patent strategies and this can affect the return to R&D and patenting consistent with creative-destruction (Cockburn and Griliches, 1988, Thesmar and Thoenig, 2000 and Greenhalgh, Mark Rogers, 2006).

In more competitive innovation markets, there exist more potential innovators, each of which has non-trivial expectations of replacing the current monopolist. If innovation markets are less competitive, incumbent firms may be able to earn rents for a considerable time without being replaced and having its rents destroyed. Because innovation markets do not ‘clear’ at observable price and output levels, determining their competitiveness is difficult. Megna and Klock (1993) find that rival patenting negatively affects Tobin’s *q* for firms in the semiconductor industry. McGahan and Silverman (2006) show that financial market value is negatively associated with “important” patenting by outside inventors. We similarly exploit various measures related to firms’ intellectual property (IP) as indicative of innovation output and evolution. In particular, we identify patent classifications with areas of science or innovation market to measure the number of firms that participate, the level of concentration, and the evolution over time. Moreover, patent citations can both indicate the importance of the cited IP and provide a measure of connectedness between firms’ research portfolios. Many studies incorporate forward citations – future citations to a firm’s current patent portfolio – when analyzing annual data on Tobin’s *q* (Bitzer, 2005 and Deng, 2007). We also analyze backward citations – current citations to a firm’s patent portfolio – in an analysis of daily stock market returns.

Our proposed empirical methodology relates the market return to various citation patterns based on an event study methodology. Event study methodologies have been successful in finding significant results for financial events such as stock splits, mergers, earnings and dividends announcements and for regulatory or judicial events, such as product recalls, market approval decisions, and legal decisions. In the usual application, the researcher investigates the effects of relatively few events (often less than one hundred) that are expected to have a large impact of firm profitability. In our case, we investigate over ten thousand patent citation events, each of which is expected to have a small effect on market return. The large number of observed events and characteristics of the citation allow us to to test for more nuanced effects by type of citations.

We find general support for the methodology we propose. First, backward, but not forward, citations are related to stock market returns. This is consistent with the revelation of information about the value of a firm's patent portfolio evolving over time as these patents are cited. Second, citations to both a firm's patents and to patents in areas of science where a firm has more intellectual property, appear to signal an increase in expected future profits. Third, controlling for this signaling affect, citations from potentially competing patents tend to decrease the firm's market value. Thus, by exploiting patent classification information, we find evidence of rivalry among innovators for marketable technologies emanating from distinct areas of science.

II. A Model of Creative-Destruction

To help solidify what we can measure and what we cannot, we sketch a simple model that relates a firm's Research and Development (R&D) investment to its market value through its accumulated intellectual property. Our application to the pharmaceutical industry borrows from elements of the “Creative-Destruction” ideas of Schumpeter (1942). Firms compete by researching new promising chemicals and acquire a portfolio of patents along the way. Many of these research projects will not yield viable products. Moreover, those that embody promising paths to profitability could be superseded by the outcomes of later research projects by other firms. This stochastic process is characterized by firms generating continuing streams of R&D outcomes that sometimes build on each other and sometimes supplant each other.

In our model, firms can invest R&D resources in every period into many related areas of science. New products emerge from the knowledge discovered in these areas of science, but they emerge stochastically and with a lag. When a new product does emerge, it will represent a flow of future revenues that may exceed future production costs. Profits from a product are capitalized when the expected net present value of these income flows exceed the investment in R&D responsible for the income flow. The market value of the firm is the present value of net income from current and expected future products summed over all products minus the R&D costs. We assume that firms choose R&D investments optimally by equating the marginal R&D costs and the expected future marginal net revenues, so as to maximize profits.

Intellectual Property (IP) represents an intermediate outcome created by a firm’s R&D investment that is an input into the development of the firm’s new marketable products. Firm *i*’s R&D expense in area of science *g* at time *t* is defined as, R_{igt} while its IP outcome is defined as IP_{igt}. A firm’s research activities at a point in time are described by the vector $\mathbf{R_{it}} = (R_{i1t}, R_{i2t},\ldots R_{iGt})$ and its intellectual property at that point in time is described by the vector $\mathbf{IP_{it}} = (IP_{i1t}, IP_{i2t},\ldots IP_{iGt})$. It is not necessary for our purposes to fully specify the IP production function. However, we imagine that IP in an area not only increases stochastically with past R&D primarily in that area but also with R&D in other related areas, $\mathbf{IP_{it}} = f(\mathrm{L}\ \mathbf{R_{it}})$ where L is the lag operator and *f* is a multivariate distribution function. It will be important for our purposes that the realization of $\mathbf{IP_{it}}$ resolves some, but not all, of the uncertainty about the viability of future products emanating from the research.

The evolution of new products is described similarly. Let $\Pi_{ij\tau}$ be the operating profits from firm *i*'s product *j* in time τ. The expected value of this product at time *t* is $EV_{ijt} = E[\Sigma_{\tau=0}\ \Pi_{ijt+\tau}/(1+r)^{\tau} \mid \mathbf{I_t}]$ where $\mathbf{I_t}$ is the information set at time *t*. The expected value of potential product *j* depends on the IP of the firm out of which product *j* might emerge. In addition, expected future profits also depend on other firms' IP in two ways. First, other firms' IP related to firm *i*'s IP may result in new products that will substitute for any of firm *i*'s products emerging from this IP. Second, other firms' IP that refers to firm *i*'s IP may signal the importance and viability of firm *i*'s research program. Technically, in this second mechanism, other firm's references to firm *i*'s IP, does not increase Π_i but expands $\mathbf{I_t}$ by providing further information regarding the distribution out of which the expectations are formed. Define $EV_{ijt} = h_j(\mathbf{IP_{it}}, \mathbf{IP_{-it}} \mid \mathbf{I_t})$ where $-i$ refers to all other firms and *h* is another multivariate distribution function. The value of firm *i* at time *t* $V_{it} = \Sigma_j\ EV_{ijt} = \Sigma_j\ h_j(\mathbf{IP_{it}}, \mathbf{IP_{-it}} \mid \mathbf{I_t})$. A product's expected value increases as the firm's IP increases and decreases as rival's substitute IP increases. In practice, if competing products do emerge, they tend to be somewhat differentiated. In this case, the magnitude of a change in own firm IP would be greater than the magnitude of an equal sized change in the IP of rival firms,

$$\frac{\partial h_i}{\partial IP_i} > -\frac{\partial h_i}{\partial IP_{-i}} > 0.$$

All of these effects are conditional upon the information set available at the time.

For the most part, the vector of R&D inputs and the profits that are related to products that subsequently emanate from these inputs are rarely observable. However, in industries in which the patent system is used extensively, many aspects of IP, an intermediate outcome, are observable. Likewise, for publically traded firms, expectations of overall firm profitability are also observable. We seek to relate changes in various measures of $\mathbf{IP_{it}}$, and changes in the information set $\mathbf{I_t}$ regarding $\mathbf{IP_{it}}$, to changes in V_{it}. Suppose that between periods *t* and *t*-1, firm *i*'s IP changed by $\Delta IP_{i1t} > 0$.The effect of this on the firm's value would be

$$\Delta V_{it} = \sum_{g=1}^{G} \frac{\partial h_i}{\partial IP_{igt}} \Delta IP_{igt} > 0$$

which, under the 'creation' aspect of Shumpeter's 'creative-destruction' concept, would be positive. In our empirical analysis below, we do not actually relate changes in a firm's value to direct changes in the patents included in firm *i*'s patent portfolio. Instead, we focus on informational changes affecting the value of this portfolio and changes in rivals' patent portfolios.

Following the existing literature, we consider a patent citation to indicate IP importance. In our model this means that $\mathbf{I_t}$ has expanded in way that puts greater probability mass on states of the world in which the cited patent generates greater future profits. First, consider a citation to firm *i*'s portfolio that has no affect on rival firms' IP:

$$\Delta V_{it} = \sum_{g=1}^{G} \frac{\partial h_i}{\partial IP_t} \frac{\partial IP_i}{\partial I_{igt}} \frac{\partial I_t}{\partial cite_{igt}} \Delta cite_{igt}$$

By assumption, citations are favorable information making the second term positive, and therefore, the whole expression positive. We consider this to also represent Schumpeterian “creation” due not to a greater quantity of patents, but from patents being revealed to be of higher quality. Second, consider a citation to firm *i*’s portfolio that also affects a rival firms’ IP:

$$\Delta V_{it} = \sum\nolimits_{g=1}^{G} \frac{\partial h_i}{\partial IP_i} \frac{\partial IP_i}{\partial I_{igt}} \frac{\partial I_t}{\partial cite_{igt}} \Delta cite_{igt} + \frac{\partial h_i}{\partial IP_{-i}} \frac{\partial IP_{-i}}{\partial I_{igt}} \frac{\partial I_t}{\partial cite_{igt}} \Delta cite_{igt}$$

Thus, a citation to firm *i* that also indicates that rival technology from firm *k* is also more valuable has two effects. The first is the positive signal as above and the second is a negative signal from an increased expectation that a rival firm’s technology will serve the same market. In the analysis below, we identify this effect with patent citations where the citing patent is from the same area of science. We consider this second effect to indicate Schumpeterian “destruction” of firm value due to innovation market rivalry. Note that, if the marginal effect of rival IP is of smaller magnitude than of own IP, the net effect would still be positive.

III. Patent Methodology

In R&D intensive industries, patent grants often indicate the potential that new products will be introduced in the future. To the extent that these potential products will be profitable to a firm, the patent grant will be associated with a greater probability of the capitalized value of this future profit stream as reflected in an abnormal return to holding equity in the firm. Since patents often will not yield future profitable products, a single patent event will have only a small effect on market value. The patent system, however, does, provide some indicators of which patents are more likely to generate future profits. One area of research into patent ‘importance’ has explored citations to a patent as indicating information that the discovery is more likely to be profitable (Trajtenberg, 1990 and Hall, Jaffe, and Trajtenberg, 2005). There are well known problems with using citations to patents as a measure of patent value. Cockburn and Griliches (1988) show how a patents value depends on industry conditions and firm-specific factors. Lanjouw and Schankerman (2004) show more precise estimates can be obtained with multiple measures of patent “quality.”

We expand the types of patent citations to include citations to a firm’s areas of research to test for the hypothesized differing effects by different types of patent citations. This approach borrows ideas from event study methodology based on the Efficient Market Hypothesis in modern finance theory. Profit-seeking through stock trades causes security prices to adjust to new information until stock prices reflect the updated expected discounted value of holding the security. Information about increased future profits from patent citations will be incorporated into the return to holding the security. We relate the daily abnormal return for about two dozen securities over 15 years to emerging information regarding citation patterns.

Information from the stock market’s reaction to firms’ patents has the potential to identify the stochastic nature of project success, including the potential superseding, or “leap-frogging,” of one technology by another. Important new discoveries, as identified in patent grants, should lead to increased expectations of future products and profits for the firm and thus will tend to increase stock market value. The subsequent pattern of citations to a patent could identify “news” about the rent creation and destruction process. A potential problem is that it the economic researcher may not observe as much information as market participants regarding which specific patents represent important discoveries and which represent dead-ends. Citations are a measure of patent importance that becomes observable to the researcher much later than the actual patent granting event. We conjecture that, at the time a patent garners another citation, the market value of the firm owning this intellectual property will increase, thus indicating the expectation of the creation of quasi-rents.

Likewise, as indicated above, citations may also identify the destruction of these quasi-rents, as a subsequent new patent may signal an increase in the value of a competing technology. Apart from signaling importance, a citation from a later patent that is classified into the same area of science is more likely to replace the cited technology than a citation from outside that area of science. If so, controlling for the signal of importance that increases market value, a citation from the same area of science would tend to reduce the cited firm's market value.

We create specific measures from patent citations that we identify with the "importance" of a firm's patent portfolio. Lanjouw and Schankerman (2004) show that multiple measures of importance reduce the variance in the estimate of patent's value. Since we require a systematic measure linking characteristics of both the cited and citing firm, we concentrate on patent citations exclusively. For each citation from one patent to another patent, we distinguish between the grant dates of the citing patent and the cited patent. Consider the citations to a firm's patents, $Cite_{ijts}$, where *i* refers to the patenting firm, *j* indexes the citing firm, *t* indexes the cited patents grant date and *s* indexes the citing patent's grant date. For the cited patent date and a cited patent firm, and keeping to convention (Trajtenberg, Henderson, Jaffe, pp.56), we label *forward citations* as the sum of all future citations for a specific firm's patents, that is, $ForCite_{it} = \Sigma_j\Sigma_s Cite_{ijts}$. Likewise, *backward citations* are the sum of all citations to all patents previously granted to the firm, that is, $BackCite_{is} = \Sigma_j\Sigma_t\ Cite_{ijts}$. Forward citations then refer to how "important" the patent will eventually be revealed to be while backward citations refer to how "important" past patents are now revealed to be. The key distinction between them is the timing of when this information is revealed to market participants.

In addition to direct citations, we also identify indirect citation to an area of research where firms are relatively stronger or weaker. Parchomovsky and Wagner (2005) argue that a patent's value is enhanced as part of a research portfolio as opposed to its stand alone value. For each patent, we identify the International Patent Classification (IPC) to which the patent is assigned. As opposed to the US Patent Classification System, the IPC system is a multilayered, hierarchical classification system. We consider IPC groups lower in the hierarchy to represent research areas that are closer to each other. For each patent granted to firm, *i*, IPC sub-group, *g*, and year, *y*, we define the sum $Area_{igy}$ as the number of patents granted to firm *i* in year *y* that were classified in area *g*. We then calculate the share of patents in the group that were granted to the firm over the past five years,

$$AreaSh_{igy} = \sum_{r=0}^{4} Area_{igy-r} \Big/ \sum_{j} \sum_{r=0}^{4} Area_{jgy-r}.$$

We consider firms with higher relative shares in a specific IPC group at a point in time to have demonstrated more expertise in that area of science. We take the vector of area shares $\boldsymbol{AreaSh_{iy}}$ = ($AreaSh_{i1y}$, … $AreaSh_{iGy}$) as describing firm *i*'s IP portfolio in year *y*. We define $citearea_{jgs}$ as a citation from firm *j* at time *s* to any patent in area *g*. Any new patents citing patents in an IPC group may reveal information about the value of firms that have substantial expertise in that area. We attempt to capture this with a measure of the sum of the interaction, $CiteGrp_{is} = \Sigma_j \Sigma_g CiteArea_{jgs} \times AreaSh_{igs}$. One can think of $CiteGrp_{is}$ as measuring "near miss" citations.

Finally, we attempt to develop a measure identifying patent citations that may indicate a technology that is more likely to compete with the cited technology. We do this by again exploiting the patent classification information. In our data, a little over one-third of all patent citations are classified into least one ICL sub-group in common with the cited patent. We conjecture that these patents are more likely to represent a potential competing technology than patents that share no ICL sub-groups. We interact this same ICL information with our $BackCite_{is}$ and $CiteGrp_{is}$ measures to yield $BackCiteSame_{is}$ and $CiteGrpSame_{is}$.

Our tests of hypotheses are conducted by relating firm *i*'s abnormal stock market return on date *s*, $abret_{it}$, to various citations measures for over different event windows.[2] The basic estimating equation is,

$$abret_{it} = \delta_i + \sum_{-w}^{w} \beta_w Citation_{it+w} + \varepsilon_{it}$$

where *w* indicates the number of days in the event window. The δ terms measure fixed firm effects while the β terms measure the importance of the citation measure. In most specifications, we include multiple citation measures. This methodology differs somewhat from typical event studies due to the sheer volume of events. In our sample, there are over 14,000 backward citations occurring on over 5,300 dates. Due to this, we allow for multiple similar events to occur on a given date by counting the number of citation events for a firm on a date. Different event windows are then accommodated by including daily leads and lags of the citation variables.

A key assumption of the analysis is that citations represent "news" about the importance of a new technology. The validity of this assumption will depend on whether this "news" is observable only to industry participants or whether it can be inferred by the economic researcher. The distinction between forward and backward citations provides a partial test of this condition. Suppose the "news" of a patent's importance is fully appreciated by industry participants upon the granting of the patent. In this case, the eventual future citation at time *s* merely confirms what is known at time *t*. This would be indicated by a positive significant effect for *ForCite* and no effect for *BackCite*. However, suppose that industry participants are as unaware of the

[2] That is, its return adjusted for co-movements with the market portfolio using a standard CAPM, or β, model.

importance of a patent at the time of a patent's granting as the economic researcher and only become informed when "news" evolves in the form of future citations. This would be indicated by a negligible or zero effect for *ForCite* and positive and significant effect for *BackCite*. Thus, it is possible to address how information about innovation evolves in this industry and whether it evolves in a way consistent with the methodology.[3]

IV. Patent and Stock Return Data for the Pharmaceutical Industry

We primarily use data from two sources: the NBER patent master file and data on abnormal returns from the Center for Research in Security Prices (CRSP). However, first we obtained a list of pharmaceutical patents from the US Patent and Trademark Office (USPTO). This was acquired by extracting patents granted from 1976 on with International Classification (ICL) codes beginning with "A61K" or "Preparations for Medical, Dental, or Toilet Purposes."[4] This yielded a total of 80,243 patents. Within this set, there are 455 unique groups and subgroups designations. These groups may differ in their breadth of coverage and in research activity as indicated by the number of patents. Table 1 indicates the number of patents by year and the percent of groups with various numbers of patents awarded in that group. In every year, the modal number of patents in a group/subgroup is zero. However, the number of patents granted in a year grew precipitously over the sample, and, as a consequence, more patents were granted in more groups.

[3] The estimation results discussed below suggest that the latter interpretation is correct. That is, industry participants are not much better informed than non-participant researchers.
[4] These data were available at http://patft.uspto.gov/netahtml/PTO/search-adv.htm.

This patent information was merged with the NBER master patent data files described in detail in Hall, Jaffe, and Trajtenberg (2001).[5] These files contain information about all patents granted by the US Patent and Trademark Office (USPTO) from1963 through 1999 and all citations for patents granted from 1975 through 1999. Among them, we could match the patent assignee with the name or subsidiary name to one of 76 publically traded pharmaceutical firms for 57,314 patents. Due to severe censoring of backward and forward citations at the beginning and end of the samples, we omit the first and last five years of data which limits our analysis to the 1980 to 1995 period (more on this below). Lanjouw and Schankerman (1999) found some gain but no significance for drugs to extend the citation span beyond five years. We further restricted our sample to firms with at least 100 backward citations. The resulting sample includes the 23 firms listed in table 2. These represent almost all of the larger R&D intensive firms associated with the US pharmaceutical industry.

Patent citations typically increase over the first few years after patent grant and then taper off. This means that we observe a smaller fraction of a patent's forward citations for patents granted in the years toward the end of the sample. Similarly, because of the way the citation data set was constructed, we do not observe many of the backward citations for patents granted toward the beginning of the sample. In addition, there has been a steady growth in the number of patents granted each year (Marco, 2007). This could be due to increased research activity, greater use of the patent system or declining standards for patentable ideas. For all these reasons, citations that occur in different years are not directly comparable measures of a patent's "importance." Figure 1 displays this year-to-year variation in forward and backward citations. Instead of using these "raw" citation counts, we deflate each citation variable by the mean of the

[5] These data were available at http://www.nber.org/patents/.

variable for the year. This normalizes values so that the sum of all citations in a year is as 'important' as any other year. Table 3 reports sample statistics for the final sample.

V. Regression Results

Table 4 reports regression coefficients for various specifications for a one day window around a citation event. Column (1) indicates that forward citations, the sum of all future citations a patent will eventually receive aggregated to the date of patenting, has a positive and significant effect on abnormal returns. Column (2) indicates that backward citations, the sum of patent citations to a firm's patents aggregated to the date of the citation rather than the date of the cited patent grant, has a larger effect. When both forward and backward citations enter the specification, as in columns (3), forward citations loses it statistical significance. A positive significant effect is found in column (4) for backward citations to an ICL group interacted with the firm's share of patents in the group. Columns (5) and (6) indicate these two backward citation measures are associated with positive abnormal returns but that, again, forward citations are not.

These results support with three general findings. First, they provide evidence for the general usefulness of a methodology that relates patent citations to daily stock market returns. The method is predicated on patents being of heterogeneous "importance" and the market both observing a continuous flow of granular bits of new information revealing this importance. These assumptions appear to be confirmed. Second, these results suggest only a small informational advantage, if any, to market participants over the economic researcher. That backward, and not forward, citation measures are related to value is consistent with market participants having diffuse prior expectations of the importance of a patent at the time of patenting, but updating priors as citations occur. Third, "importance" is conferred not only by direct citations to a firm's patent portfolio, but also by "near miss" citations that cite to an area of science in which the firm has already generated intellectual property.

Table 4 is generally consistent with firms receiving financial market validation from the creation of important intellectual property. In table 5, we turn to our tests of firms losing market value when their intellectual property is "destroyed" by subsequent competing intellectual property. Here, we focus on citations from patents from the same ICL, or area of science, that we claim are more likely to lead to future competing products. Column (1) indicates that the count of direct backward citations (creation) is positive and significant and the count of these citations in which the citing patent shares an ICL with the cited patent (destruction) is negative and significant. Column (2) repeats the analysis for indirect citations to groups but reports a negative but insignificant "destructive" estimate. Columns (3), (4) and (5) introduce combinations of direct and indirect citations measures and generally confirm the results of columns (1) and (2). While there is strong support for IP creating rents, the results for IP destroying rents are weaker.

Table 6 repeats columns (1), (3), and (5) for a three day event window. As explained above, this is accomplished by introducing lags and leads around the event date. In general, the pattern of abnormal returns tends to continue into the day after the event but is not anticipated in the previous day. This is further evidence that the event represents "news" to market participants. The estimates of cumulative abnormal returns over the three day window are reported in the bottom panel. In general, relative to table 5, the magnitudes tend to be larger and the hypotheses of parameters equal to zero can be rejected with greater confidence. However, the destruction test for the citation to an ICL group is not significant in table 6.

The magnitudes of these effects are not large but are not insignificant. The coefficient estimates represent the percentage change from one additional citation. The normalization of the citation data so as to avoid the citation inflation issue involved dividing each observation value by that variables mean value. As a consequence, the mean value of each variable is exactly one. Over a year with 250 trading days, Table 6 implies that if the average firm garnered no patent citations at all, its annual return would be about 2.25% lower. Phrased differently, the importance of a firm's patent portfolio, as revealed by patent citations, can account for just over 10% of the nominal return to pharmaceutical firms. It is doubtful that this one of many possible sources of information about a firm's future profitability could account for much more.

VI. Conclusion

We proposed a method of analyzing competition in innovation markets based on a model of creative destruction. This method centers on uncovering the stock market return to a firm's patent being cited in subsequent patent filings. We argue that patent citations related to a firm's patent, especially to a patent where a firm has a prominent IP portfolio, should increase market value. Such citations reflect IP importance and hence value creation. We further argue that patent citations from technologies that are more likely to generate competing products should decrease market value. Consequently, holding the above effect constant, we find a reduction in market value from citations where the citing patent shares the same area of science the cited patent.

Our specific findings relate to the nature of competition in innovative industries. The pharmaceutical industry, in particular, is not characterized by much competition in product markets. Instead, firms compete by conducting R&D to develop new products that could replace existing products. Rather than competition *in the market*, we find evidence consistent with competition *for the market*.

Our analysis contributes to methods of analysis of competitive dynamics in innovation markets in two ways. First, like previous studies, we investigate the return to various patenting activities. Most analyses relate patent information aggregated to the calendar year to annual financial variables such as Tobin's *q* (Megna and Klock, 1993, Lanjouw and Schankerman, 2004, McGahan and Silverman, 2006). Instead, we relate daily patent information to the daily abnormal returns to holding equity in the firm. Both methods use the value of a firm as revealed by stock market participants. Because of the increase in the number of observed events, daily returns are likely to allow for more nuanced views of the determinants of market value due to the particulars of the cited and citing patents.

Second, we exploit information about the area of science a patent represents. Patent classifications have not been readily available to researchers.[6] We obtained this International Patent Classifications only by repeatedly searching the USPTO website and merging the collected data with existing datasets. These data allow for a measure of the degree of closeness of one patent to another in terms of the science that they represent. In particular, they allow for a definition of an area of science that can be analyzed independently from product markets. While our specific analysis links citations to an area to a firm's prominence in the area, these areas could easily be used for other research questions.

This method has only become available due to recent efforts to systematically digitize patent information. These methods, suitably extended, could be applied to other research

[6] The NBER patent file update will contain patent classification information.

questions and other industries. It may be possible to identify government policy interventions that were more or less conducive to generating a continuing flow of innovations. For example, the insights behind our method are general enough that they could be incorporated into an evaluation of the social costs and benefits to policies that encourage innovation and/or encourage longer periods of monopolization.

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Figure 1
Total Citations by Year

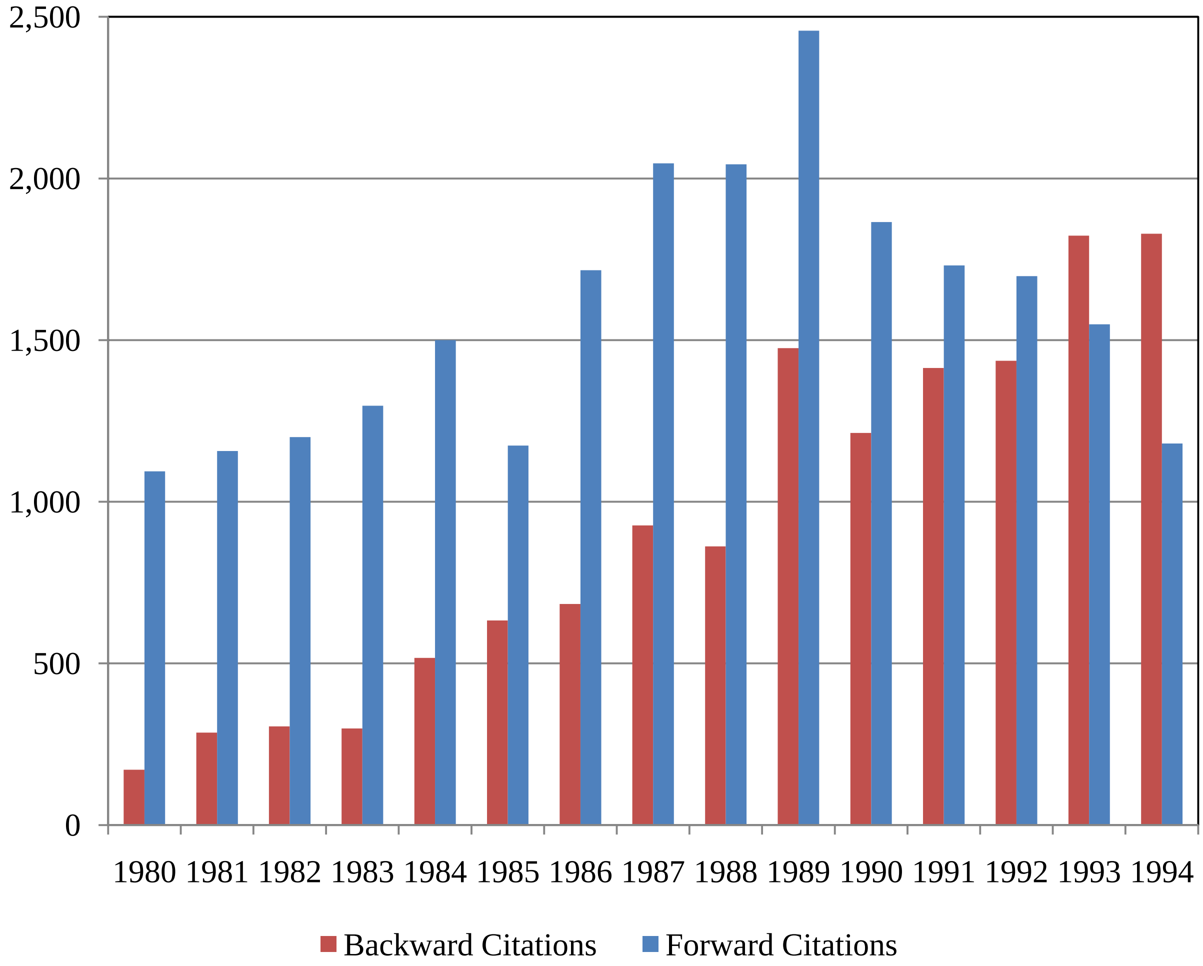

Table 1
Number of IPC Groups by Year and the Percent of Patents Granted in the Group

Year	0	1	2	3-4	5-7	8-15	16-25	26-50	50-100	100-441	Total Patents
1976	65.7%	9.7%	5.3%	5.5%	5.7%	3.7%	2.2%	2.2%	0.0%	0.0%	1,021
1977	62.2%	9.5%	7.0%	5.5%	4.2%	5.3%	3.7%	2.4%	0.2%	0.0%	1,379
1978	61.8%	7.5%	8.4%	6.6%	4.0%	5.3%	2.6%	2.9%	1.1%	0.0%	1,611
1979	62.0%	7.9%	7.5%	7.3%	4.8%	4.2%	3.3%	2.4%	0.7%	0.0%	1,422
1980	59.1%	8.8%	6.8%	7.3%	5.3%	5.3%	3.5%	2.6%	1.1%	0.2%	1,783
1981	53.0%	10.1%	9.7%	8.1%	5.7%	6.6%	2.4%	3.1%	1.3%	0.0%	1,892
1982	53.6%	10.8%	6.8%	7.5%	6.6%	7.7%	2.4%	3.5%	1.1%	0.0%	1,852
1983	58.0%	9.9%	5.9%	7.7%	5.7%	6.4%	2.6%	2.4%	1.3%	0.0%	1,677
1984	52.5%	12.3%	7.5%	7.0%	6.2%	7.5%	2.0%	2.9%	2.2%	0.0%	2,100
1985	53.0%	12.7%	6.2%	6.4%	6.6%	7.0%	3.5%	2.6%	1.5%	0.4%	2,082
1986	53.8%	9.5%	5.9%	8.6%	6.6%	8.1%	2.4%	3.1%	2.0%	0.0%	2,152
1987	48.4%	12.5%	6.8%	7.7%	7.7%	7.9%	3.3%	3.1%	2.0%	0.7%	2,582
1988	49.0%	11.9%	6.4%	8.1%	8.6%	7.0%	3.7%	2.4%	2.4%	0.4%	2,602
1989	46.2%	11.2%	7.7%	5.9%	7.9%	8.1%	4.6%	4.8%	2.6%	0.9%	3,434
1990	45.1%	14.7%	7.3%	7.0%	7.0%	8.1%	3.7%	4.4%	2.0%	0.7%	2,951
1991	45.1%	10.5%	7.9%	5.9%	8.6%	7.0%	6.2%	5.7%	2.0%	1.1%	3,460
1992	43.5%	11.4%	8.1%	8.1%	6.4%	9.9%	5.1%	4.8%	2.0%	0.7%	3,265
1993	43.3%	11.0%	6.2%	8.6%	7.3%	11.6%	2.4%	6.2%	2.4%	1.1%	3,623
1994	42.0%	12.7%	6.8%	10.1%	5.7%	10.8%	3.3%	5.3%	2.0%	1.3%	3,544
1995	26.4%	16.7%	8.6%	9.9%	11.9%	12.3%	5.1%	4.6%	2.6%	2.0%	4,447
1996	19.3%	14.1%	10.1%	11.9%	11.0%	14.9%	6.8%	5.1%	4.4%	2.4%	5,896
1997	17.6%	11.2%	9.7%	11.9%	11.6%	13.2%	9.7%	6.8%	5.1%	3.3%	7,743
1998	18.0%	10.3%	8.6%	9.5%	11.0%	15.2%	9.7%	7.5%	6.4%	4.0%	8,659
1999	19.1%	10.1%	7.0%	10.5%	12.3%	13.2%	8.6%	8.6%	6.4%	4.2%	9,066

The sample is constrained to patents granted by the US PTO that are classified in one of the 445 IPC groups under the general heading of A61K, “Preparations for Medical, Dental, or Toilet Purposes.”

Table 2
Summary of Sample Firms, Dates and Citations

Permno	Company Name	Citations		Beg. Date	End Date	Obs.
		Backward	Forward			
22592	3M	118	299	1/2/1980	12/30/1994	3,793
75646	ALLERGAN	169	838	1/2/1990	12/30/1994	1,265
64856	ALZA	1,139	1,718	6/9/1983	12/30/1994	2,924
23341	AMERICAN CYANAMID	546	836	1/2/1980	11/22/1994	3,767
15667	AMERICAN HOME	522	1,078	1/2/1980	12/30/1994	3,793
19393	BRISTOL MYERS	1,677	2,506	1/2/1980	12/30/1994	3,793
18729	COLGATE PALMOLIVE	165	224	1/2/1980	12/30/1994	3,793
20626	DOW CHEMICAL	153	180	1/2/1980	12/30/1994	3,793
11703	DU PONT	353	712	1/2/1980	12/30/1994	3,793
75064	GLAXO	285	399	6/11/1987	12/30/1994	1,912
33072	ICI	481	870	1/2/1980	12/30/1994	3,388
22111	JOHNSON & JOHNSON	109	153	1/2/1980	12/30/1994	3,793
50876	LILLY	877	1,642	1/2/1980	12/30/1994	3,792
47837	MARION MERRELL	139	489	1/2/1980	12/30/1994	3,793
22752	MERCK	2,384	4,153	1/2/1980	12/30/1994	3,793
21936	PFIZER	946	1,374	1/2/1980	12/30/1994	3,793
18163	PROCTER & GAMBLE	502	826	1/2/1980	12/30/1994	3,793
39570	RHONE POULENC	504	708	1/2/1980	12/30/1994	3,793
25013	SCHERING PLOUGH	416	948	1/2/1980	12/30/1994	3,793
26390	SMITHKLINE	374	366	1/2/1980	7/26/1989	2,419
37102	SYNTEX	424	804	1/2/1980	10/28/1994	3,750
26681	UPJOHN	481	509	1/2/1980	12/30/1994	3,793
24678	WARNER LAMBERT	1,110	2,077	1/2/1980	12/30/1994	3,793

Permno is the identifier from CRSP. Beginning and end dates refer to the sample period during which CRSP contains valid values for the beta excess returns. Citation dates refers to them number of distinct dates during the sample period on which the firm received a citation. A citation date may be associated with multiple citations. Forward citations refer to the grant dates of the patent being cited and backward citations refer to the grant dates of the citing patent.

Table 3
Summary Statistics

Variable	Mean	Standard Dev.	Min	Max
Daily Return (%)	0.078	1.822	-32.068	54.098
Beta Excess Return (%)	-0.004	1.597	-21.971	53.493
Unadjusted				
Forward Citations	0.296	2.492	0.000	187.000
Backward Citations	0.173	1.031	0.000	120.000
Backward Citations to Group	0.015	0.082	0.000	2.510
Backward Citations Same ICL	0.085	0.587	0.000	34.000
Backward Citations to Group Same ICL	0.007	0.052	0.000	2.000
Adjusted				
Forward Citations	1.000	8.505	0.000	749.442
Backward Citations	1.000	5.955	0.000	442.170
Backward Citations to Group	1.000	5.351	0.000	170.711
Backward Citations Same ICL	1.000	7.104	0.000	346.450
Backward Citations to Group Same ICL	1.000	7.446	0.000	350.530

Summary statistics are for a sample of 80,112 daily observations for 23 firms from 1980 to 1995. Bottom panel variables are adjusted for general secular trends in citation counts.

Table 4
The Effects of Forward and Backward Patent Citations on Abnormal Returns
One Day Window

	(1)	(2)	(3)	(4)	(5)	(6)
Forward Citations	0.0016*		0.0011			0.0009
	(0.0007)		(0.0007)			(0.0007)
Backward Citations		0.0030**	0.0025**		0.00230*	0.0021*
		(0.0009)	(0.0010)		(0.0010)	(0.0010)
Backward Citations to Group				0.00306**	0.00241*	0.0022*
				(0.0010)	(0.0010)	(0.0010)
Constant	-0.0051	-0.0065	-0.0071	-0.0066	-0.0082	-0.0087
	(0.0057)	(0.0057)	(0.0057)	(0.0057)	(0.0058)	(0.0058)
R-squared	0.0001	0.0001	0.0002	0.0001	0.0002	0.0002

Robust standard errors in parentheses. Regressions include 80,112 daily observations for 23 firms. + significant at 10%; * significant at 5%; ** significant at 1%

Table 5
The Effects of Citations from Same ICL on Abnormal Returns
One Day Window

	(1)	(2)	(3)	(4)	(5)
Backward Citations	0.0056**		0.0045**	0.0020*	0.0045**
	(0.0016)		(0.0017)	(0.0010)	(0.0017)
Backward Citations Same ICL	-0.0026*		-0.0026+		-0.0025+
	(0.0013)		(0.0013)		(0.0013)
Backward Citations to Group		0.0047**	0.0035**	0.0041**	0.0039*
		(0.0015)	(0.0012)	(0.0016)	(0.0016)
Backward Citations to Group Same ICL		-0.0006		-0.0006	-0.0005
		(0.0009)		(0.0009)	(0.0009)
Constant	-0.0065	-0.0077	-0.0090	-0.0090	-0.0089
	(0.0057)	(0.0057)	(0.0058)	(0.0058)	(0.0058)
R-squared	0.0002	0.0002	0.0003	0.0003	0.0003

Robust standard errors in parentheses. Regressions include 80,112 daily observations for 23 firms. + significant at 10%; * significant at 5%; ** significant at 1%

Table 6
The Effects of Citations to ICL Group on Abnormal Returns
Three Day Window

	coef.	s.e.	coef.	s.e.	coef.	s.e.
Backward Citations						
Lag 1	-0.0007	(0.0017)	-0.0004	(0.0017)	-0.0003	(0.0017)
Current	0.0057**	(0.0016)	0.0051**	(0.0017)	0.0050**	(0.0017)
Lead 1	0.0062**	(0.0014)	0.0056**	(0.0014)	0.0057**	(0.0014)
Backward Citations Same ICL						
Lag 1	-0.0003	(0.0014)	-0.0003	(0.0014)	-0.0006	(0.0014)
Current	-0.0027*	(0.0013)	-0.0027*	(0.0013)	-0.0025*	(0.0013)
Lead 1	-0.0025*	(0.0012)	-0.0025*	(0.0012)	-0.0027*	(0.0012)
Backward Citations to Group						
Lag 1			-0.0006	(0.0010)	-0.0026*	(0.0012)
Current			0.0024*	(0.0010)	0.0040**	(0.0013)
Lead 1			0.0024*	(0.0010)	0.0010	(0.0013)
Backward Citations to Group Same ICL						
Lag 1					0.0024*	(0.0010)
Current					-0.0018*	(0.0009)
Lead 1					0.0016*	(0.0008)
Constant	-0.0087	(0.0059)	-0.0121*	(0.0061)	-0.0123*	(0.0061)
R-squared	0.0004		0.0005		0.0007	

Sum of Coefficients						
Backward Citations	0.0111**	(0.0027)	0.0103**	(0.0028)	0.0104**	(0.0028)
Backward Citations Same ICL	-0.0058*	(0.0024)	-0.0056*	(0.0025)	-0.0054*	(0.0025)
Backward Citations to Group			0.0042*	(0.0018)	0.0024	(0.0022)
Backward Citations to Group Same ICL					0.0021	(0.0015)

Robust standard errors in parentheses. Regressions include 80,066 daily observations for 23 firms. $^{+}$ significant at 10%; * significant at 5%; ** significant at 1%