"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 equity in a firm 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 their patent portfolio is cited and when there are citations to an area of science in which they are prominent. We interpret these findings consistent with "important" R&D creating value. Our tests of a patent portfolio being passed over are not consistent with value destruction.

Keywords: Patent, Competition, Event Study

JEL codes: O31, L65, G12

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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).

More competitive innovation markets contain 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, if patent classifications define an area of science, we can measure the number of firms successfully participating in an innovation market, its level of concentration, and its 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. We propose empirical tests measuring the market return for various citation patterns from an event study methodology.

We find general, but not absolute, support for the methodology we propose. We do find that stock market returns are related to patent citation patterns. Our results are consistent with the information about the value of a firm’s patent portfolio that is available to market participants evolves over time as these patents are cited. Citations to a firm’s patents and citations to an area of science in which a firm is prominent both increase the firm’s market value. However, our test for a firm's portfolio being overlooked by citing patents does not lead to a decline in market value.

II. A Model of Creative-Destruction

To help solidify what we can measure and what we cannot, we develop a simple model relating a firm's Research and Development (R&D) investment to its market value through its accumulated intellectual property. Our approach borrows from elements of a "Creative-Destruction" model of the pharmaceutical industry (Schumpeter, 1942). Firms compete by researching new promising chemicals and acquire a portfolio of patents along the way. 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. 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 process is characterized by firms generating continuous streams of stochastic 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 with a lag. When a new product does emerge, it will represent a flow of future revenues that may excess future costs. Profits from a product arise 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 costs and the expected future marginal net revenues, so as to maximize profits.

Define the Intellectual Property (IP) as 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 $EV_{ijt} = \mathrm{E}[\Sigma_{\tau=0}\ \Pi_{ijt+\tau}/(1+\mathrm{r})^{\tau}]$. 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. Define $EV_{ijt} = h_{\mathrm{j}}(\mathbf{IP_{it}}, \mathbf{IP_{-it}})$ where $-i$ refers to all other firms and *h* is another multivariate distribution function. The value of firm *i* at time *t* $V_{it} = \Sigma_j\ EV_{ijt} = \Sigma_j\ \mathrm{h_j}(\mathbf{IP_{it}}, \mathbf{IP_{-it}})$. We expect that a product's expected value increases as the firm's IP increases. Unfortunately, because rival's IP could have both 'substitution' and 'ratification' effects, sign of the rivals' IP effect is indeterminate.

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 $\mathbf{IP_{it}}$ 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

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

which, under the 'creation' aspect of Shumpeter's 'creative-destruction' concept, would be positive. Likewise, the effect of rival firms' $\Delta IP\text{-}_{i1t} > 0$ would be

$$\Delta V_{it} = \sum_{g=1}^{G} \frac{\partial hx_i}{\partial IP_{-igt}} \Delta IP_{-igt}$$

which, under the 'destruction' aspect of Shumpeter's 'creative-destruction' concept, would be negative. However, if instead this related IP from other firms merely 'signals' the importance of firm *i*'s IP, this would be positive. In our empirical work, we identify changes in V_{it} with the daily abnormal return to holding equity in the firm and we identify various measures of daily changes in $\mathbf{IP_{it}}$ with information about patent citations revealed on that specific day.

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 (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 both potentially 'good' and 'bad' news about a firm's patent portfolio. This allows for possible tests that distinguish between information related to both value creation and value destruction. This approach borrows ideas from event study methodology based on the "Efficient Market Hypothesis" (EMH) in modern finance theory. Profit-seeking through stock trades causes security prices to adjust until current prices reflect the expected discounted value of holding the security. Information about increased future profits from patent citations will be incorporated into the observed return to holding the security. We relate the daily abnormal return for over 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 increase its stock market valuation. 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 researcher may not observe the information available to market participants about which patents represent important discoveries and which represent dead-ends. A measure of patent importance does become observable to the researcher much later than the actual event. The number of future citations to a patent has been shown to be a good indicator of current expert evaluation of the underlying invention (Trajtenberg, 1990 and Hall, Jaffe, and Trajtenberg, 2005). 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 subsequent new patent may signal an increase in the value of a competing technology. A patent in a research area that overlooks the large research presence in that area by a firm might signal that the firm's technology may be becoming outdated. The new patent would be making citations to patents in the research area owned by other, competing firm, indicating that the competing firm's technology is on the ascendance. If so, such a citation pattern might reduce the market value of the overlooked firm. A confounding factor is that any citation to a research area may signal the increased importance of all patents in that area, including the overlooked patent.

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 (Trajtenburg, 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. For both backward and forward citations, we also distinguish if the citation is from a firm to itself, or a self-citation.

We also identify if the citation is to an area of research where firms are relatively stronger or weaker. 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 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,

$$AreaSh_{igy} = \sum_{r=0}^{4} Area_{igy-r} \Big/ \sum_{j} \sum_{r=1}^{4} Area_{jgy-r}.$$

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, $CiteSh_{is} = \Sigma_j \Sigma_g$ $CiteArea_{jgs}$ x $AreaSh_{igs}$. Finally, we attempt to identify patent citations that overlook this expertise. We distinguish patents that cite to an area where a firm has expertise and also cite to one of the firm's patents from those that fail to cite to any of firm's patents. To measure this, we define $CiteShCite_{is} = \Sigma_j \Sigma_g$ $CiteArea_{jgs}$ x $AreaSh_{igs}$ x $Cite_{ijts}$. This is intended to measure the marginal effect of a citation to a firm's IP in areas where the firm has substantial IP.

Our basic regression equates 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,

$$abret_{it} = \delta_i + \sum\nolimits_{-w}^{w} \beta_w ForCite_{it+w} + \sum\nolimits_{-w}^{w} \phi_w BackCite_{it+w} + \varepsilon_{it}$$

where *w* indicates the number of days in the event window. The δ terms measure fixed firm effects while the β and ϕ terms measure the importance of evolving information about the ability of a firm's R&D portfolio to create quasi-rents for the firm. In other specifications, we include *CiteSh* and *CiteShCite* measures. This specification differs somewhat from typical event studies due to the sheer volume of events. In our sample, there are over 22,000 backward citations

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

occurring on over 7,000 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 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. Its validity 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 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 use data primarily from two main sources: the NBER patent master file and data on abnormal returns from the Center for Research in Security Prices (CRSP). First, we obtained a list of pharmaceutical patents from the US Patent and Trademark Office (USPTO). This was

[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.

acquired by extracting patents granted from 1976 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.

These patents were 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 identify the name of the patent assignee of 73,099 patents, out of which we could match the name or subsidiary name with abnormal return data for 76 large pharmaceutical firms from CRSP. Due to severe censoring of backward and forward citations and 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 70 backward citations and 35 forward citations. The resulting sample includes the 22 firms listed in table 2. These represent almost all of the larger R&D intensive firms associated with the US pharmaceutical industry.

[4] These data were available at http://patft.uspto.gov/netahtml/PTO/search-adv.htm.
[5] These data were available at http://www.nber.org/patents/.

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 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 while table 5 reports the same for a three day window. Results for five day windows were generated but are not reported because estimated values became increasingly less precisely estimated. The first column of table 4 reports results from a specification that includes forward citations and self-citations, backward citations and self-citations, citations to an IPC group interacted with each firm's share of patents in the group and this measure interacted with a dummy variable indicating that one of the firm's patents was cited. Subsequent columns omit various combinations of these variables in order to judge the model's sensitivity to specific variables.

Across all specifications in table 4, forward citations are never statistically significantly different from zero. In contrast, backward citations are often statistically significantly different from zero, including specifications that include forward citations. Together, these results suggest that market participants are not able to gauge the importance of a patent at the time it is granted but rather infer increased importance at the time that some other research builds upon it. Across specifications, market value is estimated to increase by 19% to 35% for every 1,000 citations. With the sample average of 0.291 backward citations per day and assuming 250 trading days per year, this implies that backward citations account for an average of 1.4% to 2.6% in annual return to holding equity in a firm in the sample.

Our estimates indicate that market value increases with each backward citation but not with backward self-citations. We cannot reject the null hypothesis that the sum of the backward citation and backward self-citation coefficients is different from zero at the usual confidence levels. Self-citations may not indicate importance due to firms responding to other patenting incentives such as creating a patent fence.

Our main focus is to measure the effect of citations to research areas in which firms have strong research portfolios, when the firm is not itself cited and when it is. These are defined by the variables *CiteSh* and *CiteShCite* above and are measured by the number of IPC area citations on a date times each firm's share of patents in the area times a dummy for one of the firm's patents being cited. Across all specifications our measure of *CiteSh* is positive and significant while our measure of *CiteShCite* is not significantly different from zero. The magnitudes range from 36% to 42% increase in market value for every 1,000 citations times IPC area share. Since the sample average of the variable is 0.276, assuming 250 trading days per year, this implies that citations to an area in which a firm is strong accounts for an average of 2.5% to 3.1% in annual return to holding equity in a firm in the sample. These findings are consistent with the information value of a citation to a strong a research portfolio in an area dominating the information value that a firm's specific IP in that area was not cited. We do not find evidence of the 'destruction' of rents due to the emergence of a supplanting technology.

Changes in the estimate of the constant term across specifications of table 4 can also be informative. While the sample mean abnormal return from table 3 is negative, it is not significantly different from zero. However, when backward citations and, especially, area citations are included to the specification the intercept term becomes significantly negative. An interpretation of this result is that market value erodes for firms that fail to generate patent citations or fail to develop research areas. The estimated daily return of -0.00015 corresponds to a -3.8% annual return. These results are consistent with the phrase "falling behind by standing still." However, these estimates are considerable smaller than those of Caballero and Jaffe (1993) who find that pharmaceutical firms that fail to invent lose 25% of their market value.

Table 5 reports the sum of coefficients for the three day window beginning one day before the citation event and the standard error of this sum. In general, the same patterns found in table 4 are found here. One difference is that forward citations are now significant in the specification that excludes all other citation measures. However, the magnitude is smaller than for other citation measures and the estimated coefficient is not significant when other covariates are added to the specification. This indicates that market participants may be able to infer some of the importance of a patent when it is granted but not all and, perhaps, not as much as will be revealed over time when the patent is cited.

Another difference emerges with the backward citations. The estimated effects of backward citations are substantially larger with the three day window versus the corresponding specification with the one day window. However, the estimated effects from columns (1) and (7), specifications that include area citation measures, do not reject the null hypothesis at the 5% significance level, but do at the 10% level. At backward citation sample means, these parameter estimates correspond to an additional 1.9% to 4.2% annual return.

The largest difference has to do with the area citations. The estimated effects from table 5 are little more than double the size as were found in the one day window. The area effect corresponds to an additional 6.2% to 7.3% in annual return, again more than double the estimate from table 4.[6] However, the area citations interacted with the dummy for a patent citation is negative and significant, though only at the 10% level in column (1). The interaction with the citation corresponds to a 0.5% reduction in annual return. This puzzling result is not as expected.

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. Similarly, patent citations to an area in which a firm has a prominent IP portfolio that fails to cite one of the firm's patents represents the emergence of a new technology that may replace the technology of the passed

[6] The annualized return calculation for the intercept estimate of -0.000298 is proportionally larger in absolute terms at -7.2%.

over firm. If so, this event should lead to a decrease the firm's market value or value destruction. Our findings are only partially consistent with these hypotheses.

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. Daily returns are likely to allow for more nuanced views of the determinants of market value.

Second, we exploit information about the area of science a patent represents. Patent classifications are not readily available. 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 innovation market 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 questions and other industries. It may be able 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
Mean Number of Raw Forward and Backward Citations by Year

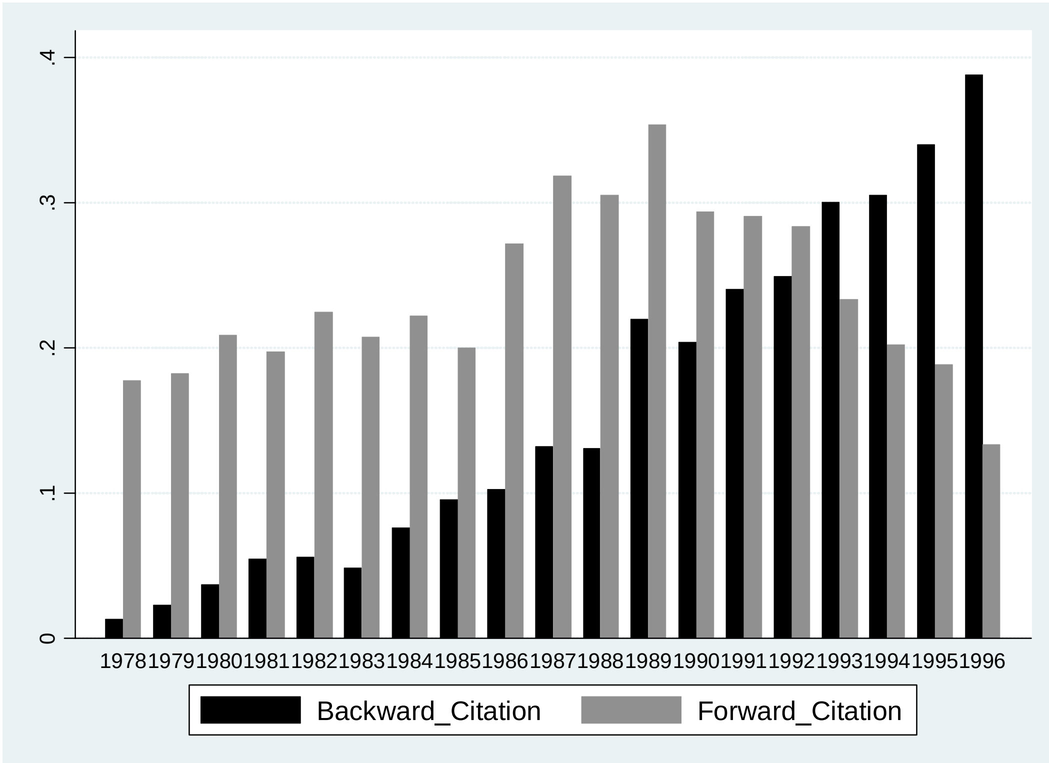

Table 1
Number of IPC Groups by Year and the Percent of Patents Granted in the Group

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	Citation Dates: Forward	Citation Dates: Backward	Beg. Date	End Date	Obs.
22592	3M	49	216	1/2/1980	12/30/1994	3,793
64856	ALZA	162	403	6/8/1983	12/30/1994	2,924
23341	AMERICAN CYANAMID	213	407	1/2/1980	12/30/1994	3,767
15667	AMERICAN HOME PRODUCTS	160	330	1/2/1980	12/30/1994	3,793
19393	BRISTOL-MYERS SQUIBB	356	621	1/2/1980	12/30/1994	3,793
18729	COLGATE-PALMOLIVE	44	251	1/2/1980	12/30/1994	3,793
20626	DOW CHEMICAL	61	173	1/2/1980	12/30/1994	3,793
11703	DU PONT	132	290	1/2/1980	12/30/1994	3,793
50876	ELI LILLY	234	488	1/2/1980	12/30/1994	3,792
75064	GLAXO WELLCOME	81	173	6/10/1987	12/30/1994	1,912
33072	ICI	163	354	1/2/1980	12/30/1994	3,388
22752	MERCK SHARP & DOHME LIMITED	482	661	1/2/1980	12/30/1994	3,793
47837	MERRELL DOW PHARMACEUTICALS	121	121	1/2/1980	12/30/1994	3,793
21936	PFIZER INC.	286	516	1/2/1980	12/30/1994	3,793
18163	PROCTER + GAMBLE	119	388	1/2/1980	12/30/1994	3,793
39570	RHONE POULENC RORER	146	270	1/2/1980	12/30/1994	3,793
25013	SCHERING	152	310	1/2/1980	12/30/1994	3,793
26390	SMITHKLINE BECKMAN	116	240	1/2/1980	7/26/1989	2,419
14592	STERLING DRUG	41	86	1/2/1980	2/29/1988	2,063
37102	SYNTEX	144	347	1/2/1980	10/28/1994	3,750
26681	UPJOHN	119	337	1/2/1980	12/30/1994	3,793
24678	WARNER-LAMBERT	277	425	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	Std. Dev.	Min	Max
Beta Excess Return (x 1,000)	-0.032	16.077	-219.706	534.934
Number of Forward Citations	0.463	3.619	0.000	253.168
Number of Forward Self Citations	0.144	1.766	0.000	223.399
Number of Backward Citations	0.291	1.394	0.000	83.534
Number of Backward Self Citations	0.109	0.834	0.000	66.296
Number of IPC Area Cites x Area Share	0.275	0.891	0.000	37.795
Number of IPC Area Cites x Area Share x Cite	0.029	0.352	0.000	29.378
Log Forward Citations	0.111	0.497	-0.440	5.538
Log Forward Self Citations	0.052	0.312	-0.276	5.414
Log Backward Citations	0.323	0.727	-0.686	4.433
Log Backward Self Citations	0.167	0.551	-0.639	4.204
Log IPC Area Cites x Area Share	0.276	0.610	-0.592	3.650
Log IPC Area Cites x Area Share x Cite	0.224	0.663	-1.141	3.403

Summary statistics are for a sample of 77,117 daily observations for 22 firms from 1980 to 1995. All citation data are adjusted for general secular trends in citation counts.

Table 4
The Effects of Various Patent Citations on Abnormal Return of Firm's Equity
One Day Window (Coefficients x 1000)

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Number of Forward Citations	-0.014	0.029		0.010		-0.015	
	(0.021)	(0.021)		(0.021)		(0.021)	
Number of Forward Self Citations	0.036	0.021		0.028		0.032	
	(0.048)	(0.049)		(0.049)		(0.048)	
Number of Backward Citations	0.193		0.348	0.340			0.192
	(0.082)*		(0.071)**	(0.071)**			(0.082)*
Number of Backward Self Citations	-0.352		-0.323	-0.339			-0.350
	(0.133)**		(0.124)**	(0.125)**			(0.132)**
Number of Area Cites x Area Share	0.362				0.437	0.442	0.359
	(0.088)**				(0.072)**	(0.074)**	(0.087)**
Number of Area Cites x Area Share x Cite	0.226				0.005	0.009	0.224
	(0.232)				(0.215)	(0.218)	(0.231)
Constant	-0.155	-0.049	-0.098	-0.103	-0.153	-0.152	-0.156
	(0.061)*	(0.058)	(0.059)+	(0.059)+	(0.061)*	(0.061)*	(0.061)*
Observations	77,117	77,117	77,117	77,117	77,117	77,117	77,117
R-squared	0.0007	0.0001	0.0004	0.0004	0.0006	0.0006	0.0007

Robust standard errors in parentheses
+ significant at 10%; * significant at 5%; ** significant at 1%

Table 5
The Effects of Various Patent Citations on Abnormal Return of Firm's Equity
Three Day Window (Coefficients x 1000)

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Number of Forward Citations	0.038	0.093		0.066		0.040	
	(0.038)	(0.036)*		(0.037)		(0.038)	
Number of Forward Self Citations	-0.054	-0.069		-0.063		-0.056	
	(0.081)	(0.082)		(0.081)		(0.081)	
Number of Backward Citations	0.257		0.565	0.549			0.259
	(0.137)+		(0.123)**	(0.123)**			(0.137)+
Number of Backward Self Citations	-0.295		-0.453	-0.482			-0.290
	(0.224)		(0.208)*	(0.209)*			(0.223)
Number of Area Cites x Area Share	0.866				1.023	1.002	0.883
	(0.164)**				(0.142)**	(0.145)**	(0.162)**
Number of Area Cites x Area Share x Cite	-0.701				-0.792	-0.826	-0.674
	(0.414)+				(0.384)*	(0.390)*	(0.411)
Constant	-0.298	-0.060	-0.143	-0.156	-0.286	-0.289	-0.294
	(0.069)**	(0.059)	(0.063)*	(0.063)*	(0.069)**	(0.069)**	(0.069)**
Observations	77,073	77,073	77,073	77,073	77,073	77,073	77,073
R-squared	0.0013	0.0001	0.0007	0.0004	0.0011	0.0012	0.0013

Robust standard errors in parentheses
+ significant at 10%; * significant at 5%; ** significant at 1%