CREATIVE DESTRUCTION IN THE PHARMACEUTICAL INDUSTRY

by

DARSHAK PRAVINCHANDRA PATEL

Presented to the Faculty of the Graduate School of

The University of Texas at Arlington in Partial Fulfillment

of the Requirements

for the Degree of

MASTER OF ARTS IN ECONOMICS

THE UNIVERSITY OF TEXAS AT ARLINGTON

MAY 2007

ACKNOWLEDGEMENTS

I like to thank Dr Ward for his full support and inspiration in helping me to complete this research. Dr Ward consistently provided his utmost knowledge with constructive suggestions to make this thesis a success. I also like to thank my committee members Dr. Craig A. Depken, II and Dr. Cagatay Koc for all their help. I thank a friend and UTA Economics Alum Mishuk Chowdhury for his help in programming.

April 21, 2007

ABSTRACT

CREATIVE DESTRUCTION IN THE PHARMACEUTICAL INDUSTRY

Publication No. _____

Darshak Pravinchandra Patel, M.A.

The University of Texas at Arlington, 2007

Supervising Professor: Michael R. Ward

Pharmaceutical firms usually patent any new innovation in terms of the chemicals they use. These innovations are then developed in to drugs which are marketed once approved by FDA. These patents have made and receive citations. Citations made by patents granted today are backward citations and citations a patent will receive in the future are forward citations. This research shows that these patent citations on have a positive effect on market value of Pharmaceutical firms related to the patent. Backward citations do not destroy company rents. In fact, backward citations, illustrate the importance of the cited patent. Multiple citations imply that other firms are trying to develop more competitive drugs and therefore reduce market share of the firm that owns the cited patent. However, more citations to the cited patent also

imply that the patent may become a blockbuster drug. Overall, this research shows that extensive R&D is positively correlated with the firm's returns.

TABLE OF CONTENTS

LIST OF ILLUSTRATIONS

LIST OF TABLES

CHAPTER 1

INTRODUCTION

Joseph Schumpeter introduced a theory concerning industry evolution in which entrepreneurs create wealth through innovation and have the economic source of their wealth destroyed by subsequent entrepreneurs. In his book Capitalism, Socialism and Democracy he called this process "Creative Destruction". He initially focused on capitalism's creative ability such as the making of cars, computers, and new markets. However, the term Creative Destruction was later formed as he realized that the new creations also diminished older creations by eliminating them or devaluing them.

1.1 Summary of the Thesis

According to Creative Destruction, old innovations diminish in value with the introduction of newer innovations. Many companies that enjoy substantial monopoly powers earning supernormal profits eventually see their profits decline as many competitive firms enter the profitable industry. This can easily be replicated in the pharmaceutical industry. This research looks at whether citations to patented drugs in the pharmaceutical industry leads to what Schumpeter termed as Creative Destruction; do citations by a citing firm destroy market returns of a cited firm? When Blockbuster drugs have their patents approved, it more than likely has positive effects on the stock returns for the firm that produces that drug. In the future, many firms will try either to

innovatively replicate the drug for a similar purpose or come up with generic brands when the patent is nearing expiration. In the early years of the patent, different firms are going to cite the patented drug to figure out a similar functioning drug. I expect these multiple citations on different days to have some kind of an effect on the stock returns of the firm that owns the patent which is cited. If my results do show that there is an adverse effect to the stock returns due to the citations, then there could be some evidence of Creative Destruction in the Pharmaceutical Industry.

1.2 Contribution of the Thesis

Little research exists that examines the elements of a Schumpeterian Creative-Destruction model of the pharmaceutical industry, but there is some literature available on this topic. Many studies have tried to quantify R&D spillovers in terms of monetary value in an attempt to directly evaluate the social returns or externalities of technological innovations. The focus on the market value of the firm as a measure of success of its innovative activity derives from the notion that R&D expenditures create intangible capital for the firm. Their impact, in the form of present value of expected returns from R&D, should therefore be reflected in the valuation of the firm by the market (Johnson 1993). According to Pakes (1984), the stock market value of the firm should respond to the expected impact of changes in its R&D activity of net cash flow. R&D expenditure is input and patents are considered as output and rents from these patents are called quasi rents. Theses quasi rents in turn affect the market value of the

firm. I intend to use other available literature to help further develop my theory and methodology.

1.3 Organization of the Thesis

The thesis is organized as follows: a review of relevant literature is in chapter two. Chapter three has explanations on Schumpeter's Creative Destruction, empirical model and hypothesized results. Chapter four has information on the collection of the data. Chapter five gives the results from the empirical model and chapter 6 is the conclusion my thesis. Finally, after the conclusion there is the Appendix.

CHAPTER 2

LITERATURE REVIEW

2.1 Literature on Pharmaceutical Industry

The hallmark of the pharmaceutical industry is to do research in order to develop new drugs to sell to the general public. This industry has grown many folds in the past two decades due to the ability of pharmaceutical firms to perform research worth billions of dollars. Around the 1940s, the pharmaceutical industry consisted of many small manufacturers who depended on naturally occurring raw materials for the manufacturing of drugs. However, the pharmaceutical industry really expanded following the discovery of the Penicillin, which was the first drug to be produced using different chemicals. The potential to use chemicals to produce medicine brought an influx of new manufacturers in the pharmaceutical industry (Teeling-Smith 1980). Many of these new entrants were from the chemical industry who wanted to take advantage of researching and developing chemicals in to drugs. The rapid growth of the pharmaceutical industry is also a result of a number of important medical advances after World War II. During the World War II, Penicillin was introduced, and was very successful. Penicillin was not patented and the pharmaceutical industry had low barriers to entry (Comanor 1964). Hence, the potential to use chemicals to produce drugs and the ability to extract rents, attracted many firms to the pharmaceutical industry. As more firms entered the industry, individual firms realized that profit margins fall and

therefore started producing differentiated products. Firms started spending millions of dollars for the discovery, development and testing of new drugs thus increasing the number of new drugs in the market. Soon firms were using different types of chemicals to produce drugs and hence producing differentiated products. Firms realized that drugs created with chemicals could be patented and, they therefore filed for patents for each research projects so as to protect their study and be able to market and promote the drug once its passed all three testing phases of the Food and Drug Administration. These patents enable firms to make supernormal profits for blockbuster drugs for the life of the patent, after which, the production of generic drugs greatly reduces the market for the specific drug.

The major concerns for pharmaceutical firms are the phases the drugs have to pass in order to be approved. Due to the strict testing procedures used by the Food and Drug Administration, firms have to wait for a number of years for their drugs to be approved. It takes more than 14 years for new chemical research to be approved by the FDA for marketing purposes (Sharma and Lacey, 2004; DiMasi, 2001). Before the early 1960s, the FDA tested new drugs only for toxicity. In 1962, the FDA changed regulations that influenced the approval of new drugs. FDA's new regulations tightened the criterion for judging drug safety and companies had to prove their claims on a drug's effects. This substantially increased the time for FDA to approve a patent application. The three testing phases that a drug undergoes is explained by the figure below[1]

---

[1] http://www.fda.gov/cder/handbook/develop.htm

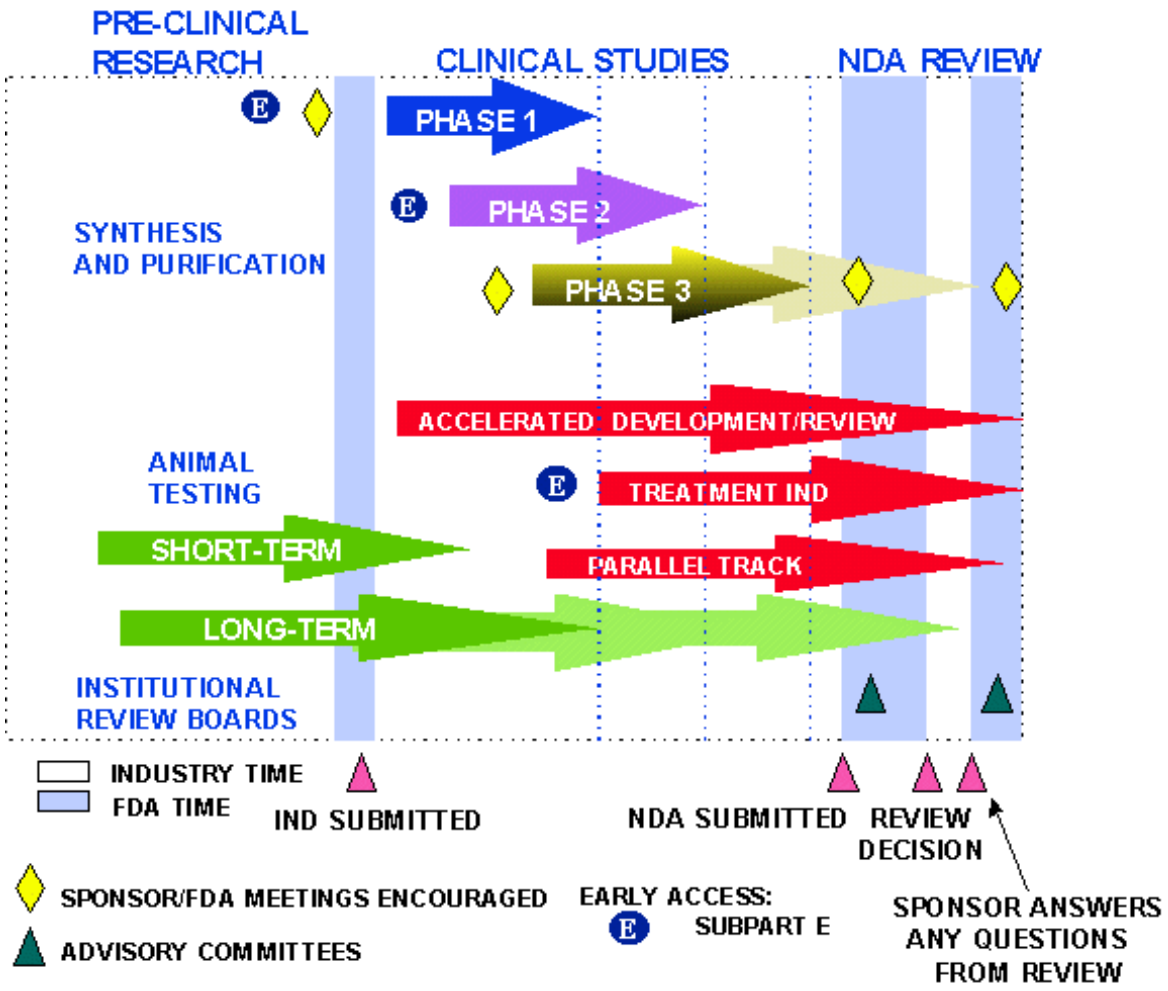

Figure 2.1: Steps from Test Tube to New Drug Application Review

The first step is synthesizing and purifying a new chemical compound. Then the chemical has to go through three phases in the clinical trials. The three phases include: (a) confirm efficacy of the chemicals on human; (b) ensure the drug's short-term safety; and (c) ensure the drug's long term safety against any adverse side effects to the use of the drug and/or chemicals. All drugs have to go through the New Drug Application

(NDA) review before a drug can be marketed. Majority of the drugs fail the clinical trials. As seen above, the drugs that do clear the three FDA testing phases,. This is where pharmaceutical firms propose to the FDA for their approval to market and sell the new drugs. The NDA contains all available information of the drug including the ingredients, testing results, animal and human reaction to drugs and the firm's marketing strategy. A drug can legally be sold once its NDA application has been approved. The section of FDA that is responsible for the approval of the NDA application is the Center for Drug Evaluation and Research (CDER). The figure below shows the benefit/risk profile of a drug product prior to approval for marketing by CDER[2]:

[2] http://www.fda.gov/cder/handbook/nda.htm

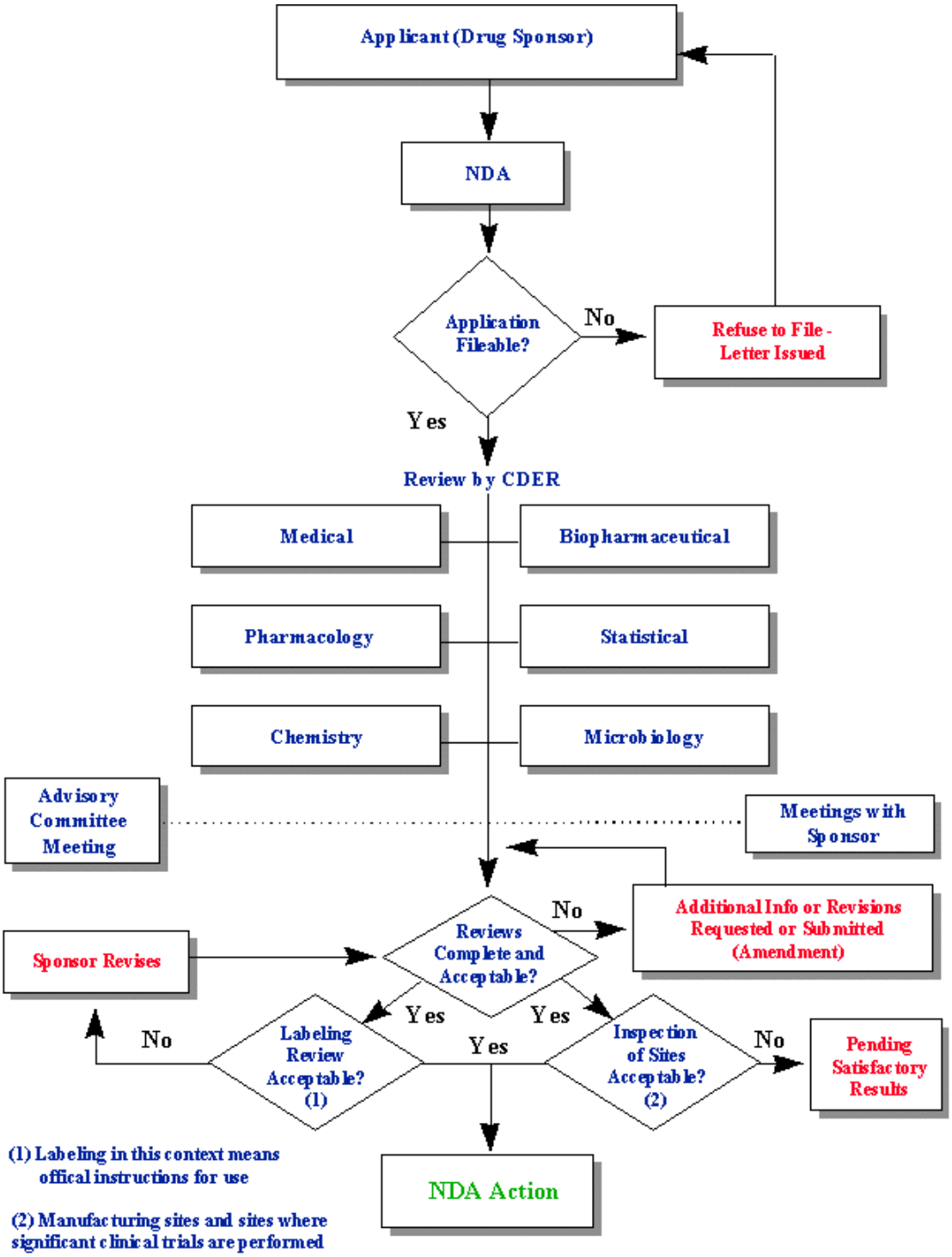

Figure 2.2: CDER's NDA application review

The new FDA regulations have led to lengthy lags in drugs approvals and have increased costs enormously. Studies have shown that the FDA amendments have raised the costs of developing new drugs and have substantially reduced R&D productivity (Baily 1972). The costs appear to be higher especially when fundamentally important drugs have been kept off the market by FDA (Dranove and Meltzer 1994). Since the 1970s, FDA has increased their efforts to identify and accelerate the development of important drugs. FDA rates drugs according to the results of their biochemical and animal studies and any foreign experience with human subjects. The drugs that rate highly among the above three dimensions were given priority or claimed as more important than other drugs. If important drugs are approved early then they are introduced to the market early. This enables the important drugs to have longer effective patent lives compared to the less important drugs. Hence, important drugs have more time in the market as a patent than drugs of lesser importance and this increases their probability to increase earnings for their respective firms. The early approval by FDA could be one way of identifying blockbuster drugs. However, it is difficult to tell if a drug will provide a major breakthrough during initial phases of the clinical trial. Some drugs that were initially thought to be blockbuster drugs are not as effective as hypothesized. Many firms and the FDA try to determine the importance of a drug while it is still under development. Firms try to forecast sales by estimating the impact of the drug on the patients. Sometimes, these initially thought blockbuster drugs do not have the same impact as forecasted and other drugs not deemed very important in the clinical phase such as Zantac has able to capture large market shares (Dranove and Meltzer

1994). Hence, forecasts do not seem to be an efficient way to pick out blockbuster drugs.

The pharmaceutical Industry has come under heavy criticism in recent years for issues such as product safety, wasteful competition, irresponsible pricing, misusing brand names, abusing patents and excessive and irresponsible sales promotions. Due to the above criticisms/problems, the FDA has become more stringent. For example, th FDA has gained control of introducing medicines in the USA and have set stringent rules in passing of the drug. This delays the introduction of the drug at the consumer's expense and even after the drug has been approved through these stringent rules, many side effects are not seen until after the drug has been circulated in the market.

Many also find that pharmaceutical companies undergo wasteful competition when they each separately perform unique research for the same diseases. Many feel that this increases the costs of research and hence raises prices for medicines. However Teeling-Smith feels that, all the pharmaceutical firms have the same goal/objective but only differ in terms of their methods of working. Historically, this approach has been very successful in discovering new drugs. Teeling-Smith found that some countries have tried to use coordinated programs where there is no competition in research have been less successful in inventing new medicines. Table 2.1 shows the success of the non coordination program of the Pharmaceutical Industry.

Table 2.1 Percentage of New Chemicals Entities Discovered and Introduced by the Pharmaceutical Industry

	Periods in which drug were introduced		
	1950-1959	1960-1969	1950-1969
Industry	86	91	88
Other	14	9	12
Total	100	100	100

Source:Teeling-Smith, George (1980). Economic Misconceptions in the Pharmaceutical Industry. Managerial and Decision Economics, Page 3, Table 1.

Due to the high level of competition, Pharmaceutical firms rely heavily on their research to come up with a unique innovation. They can then patent their innovations and look to make supernormal profits. Some firms tend to overprice their products but this may be due to the high cost of innovation rather than these firms trying to take advantage of their patents. The high cost of brand name drugs is the main reason for the price of brand name drugs to remain high even after the patent expires. As a patent expires, many firms can start imitating the chemical entities of the original research. They can do so at a cheaper cost compared to the original research and this enables the imitating firms to price the generic drugs at a much lower price than the brand name drugs. Hence, patents are very useful in helping pharmaceutical firms in recouping all the costs incurred in the original research. Some of the brand name drugs tend to perform better than expected and hence become Blockbuster Drugs. In his paper, Grabowski (1983) shows how long it takes firms that introduced drugs during the 1970 -1979 period to eventually cover up their R&D investment. It takes approximately 25 years for companies in that period to cover up their expenditure for newly introduced drugs.

There are some studies done on returns on pharmaceutical R&D activity. Those studies have shown that the rate of return to pharmaceutical R&D was very low during the 1960s and early 1970s. The mean real rate of return for new drugs at this period was between 4 to 6 percent. According to Grabowski (1983), the reason for the low rates of return was due to the strict regulations imposed by the FDA. There were findings that due to improvements in terms of technological opportunities in the pharmaceutical industry that worked around the strict regulations, most of new drugs introduced in the latter 70s and in the 1980s had much higher sales than drugs introduced in the early 70s. Furthermore, higher drug prices have helped many firms cover the R&D costs. There are many findings that show that new drugs are major source of a firms returns (Baily 1972). New drugs continue to make supernormal profits for the length of the patent. Baily (1972) found some amount of evidence showing high positive correlation between the number of patents held by a firm to the earnings of that firm. Newly patented drugs have increased earnings for firms by many folds. By 1991, pharmaceutical firms were ranked number one or two for over 24 years in terms of after-tax profit returns on stockholders equity (Scherer 1993).

2.2 Literature Review on Event Studies

An event study is where one looks at the how the market reacts to certain events. In my case, an event will be when a pharmaceutical firm has its patent application for its blockbuster drug approved. Events studies were initially used to test the efficiency of the market; it was the later used for the effects of events on the market (Salinger 1992). Event Studies methodology have been very successful in finding

significant results for many cases, for example, stock splits affects, mergers, earnings and dividends announcements, all affect firm market value. Each case mentioned above qualifies as an event and one can see their effect on the respective firm's stock returns. There are many different type of methodologies used to conduct event studies but the basic methodology used by Fama usually works for all kind of event studies. One should therefore identify the day/event of interest and get the respective data on the returns for those events (MacKinlay 1997). It is also important to create an Event Window which allows for a much better assessment of the days before and after the events. One can then run regressions to determine whether these events have any significant effects on the value of the firm. According to Henderson (1990), there are many problems with the event study methodology. The first problem is how to decide what really constitutes an event. After figuring out the actual event, it is important to define out when these events occur, that is, when does the event cause the market to react? For example, the market may react to the news of a stock split and not when the stock split actually occurs. Hence the event date would be when the news of the stock split hits the market. More problems occur when calculating the returns as there are many types of returns that can be used for these analysis. The different types of returns include: mean returns, market returns, control portfolio returns, risk adjusted returns, excess returns, and aggregate excess returns. Each of these returns is defined differently. Henderson also mentions that these days event studies need to be tested statistically and not just using charts that show market reactions to event dates. However, the simplest version of an event study will work as long as the event dates are

correctly created. The major drawback of event studies is that they are very sensitive to the timing of the information and it is hard to pinpoint the event date convincingly.

CHAPTER 3

METHODOLOGY

This research is highly motivated by Schumpeterian creative destruction model. I will be using event studies to show that there is creative destruction in the pharmaceutical industry. In this section, I explain the link between creative destruction and the pharmaceutical Industry and the method I will be using to establish this.

3.1 Creative Destruction

The quasi-rents earned by firms in the pharmaceutical industry make it an easy target for lawmakers wanting to be seen 'doing something' to reduce medical costs. At the same time, they can be seen as a 'champion of the little guy' taking on the major 'price gouging' corporations. The usual response to these accusations goes: 1) these rents are merely quasi-rents that are payments to investments in R&D made long ago and 2) competition at the R&D stage is fierce. Economists have tried time and again to translate the economic jargon of first accusation into the common vernacular and provide evidence of its veracity. Little has been done to address the second.

In my research, I am trying to detect whether a firm will lose some of its market value when another firms cites the former firm's patents. This, as explained earlier, will show the presence of creative destruction in the pharmaceutical industry. I propose to empirically test the second part by estimating the elements of a Schumpeterian

Creative-Destruction model of the pharmaceutical industry. New knowledge increases value of R&D stock but it also destroys part of it by depreciating old knowledge thereafter (Bitzer). Firms compete by researching new promising chemicals. Many of these research projects will not yield viable products. Moreover, those that embody promising paths to profitability could be super ceded by later research projects by other firms. This process is characterized by firms generating continuous streams of stochastic R&D outcomes that build on each other and sometimes surpass each other.

Information from the stock market reaction to firms' patents might identify both the stochastic nature of project success and the potential leap-frogging of technologies. Important new discoveries, as identified in patent grants, should lead to expectations of future profits for the firm and thus increase its stock market valuation. The subsequent pattern of citations to a patent could identify the rent creation and destruction process. As researchers study the innovation process in general, at the time of the granting of the patent, it is difficult for us to tell an important discovery from one that is more likely to represent a dead-end. Fortunately, we observe a measure of what future experts in the area thought of the invention. The numbers of future citations to a patent have been shown to be a good indicator of current expert evaluation of the invention (Hall, Jaffe, Trajtenberg, 2005). I expect that patents which garner more future citations will increase firm market value by a larger amount and, therefore, the creation of quasi-rents.

Likewise, citations may also identify the destruction of these quasi-rents. A future citation may signal an increase in the value of the invention at the time that the

patent is granted. But, a citation also reveals that a new patent has built upon this prior invention at the time of the citation. If building upon the old invention is associated with supplanting it, the market value of the original firm should fall at the time that another firm cites its patent. Thus, the same citation would both increase the market value of a firm at the time that the cited patent was granted and decrease its market value at the time that the citing patent was granted.

To find the citations, I used the patents and citations database and further looked for all the references made to a particular patent number in the US patent website. The US patent website provided the citing patent number, the application and approval dates, and the assignees. The approval dates of the citing patents were chosen as the event dates. This patent and citation dataset was then merged with the returns dataset from the CRSP database to provide enough information to test the hypothesis.

3.2 Hypothesis

All inventors have to cite every patent related to their research in their applications. When an application is completed, a patent examiner ensures all the related patents are cited appropriately. Hence, it is easier to obtain all the citations to and by any one patent. A citing firm is a firm that cites a patent of another firm. A cited firm is a firm whose patent has been cited by the citing firm. Forward citations occur on the date that the cited patent is granted and refers to the number of citations a patent will eventually receive. Backward citations occur on the date that the citing patent is granted and refers to the number of patents on that date that cite to any patent held by the assignee of the cited patent. Hence, this research considers the number of patents,

forward citations and backward citations. This research is trying to look at whether the citing firm causes the market value of the cited firm to rise at the time of the citation. In other words, the research is looking at the effect of the forward citations on the market value of the patent being cited. At the same time, it looks at whether the market value of the cited firm falls when the citing patent is granted. Again, this research is looking at the effect of backward citations on the market value of the cited firm. The result of this research is important as it helps pharmaceutical firms realize that their supernormal profits from the distribution of blockbuster drugs may not last very long. Furthermore, firms realize the importance of research and development to be successful in the pharmaceutical industry. I hypothesize that, forward citations, will have positive effects on the returns of the cited patent's firm as a high number of future citations may indicate that the cited patent is a potential blockbuster. At the same time backward citations will have a negative effect on the returns of the cited firm especially if the citations destroy rents when the citing patent is granted.

If a patent that has a high number of forward citations over a long time span this indicates that the innovation could be a blockbuster drug or that the research made significant discoveries. High number of frequent citations to a certain patent also indicates that the patent has been identified as being very important. Hence, this research has many important implications in that this would indicate the extent at which old innovations or patented drugs are replaced by successive innovations by R&D competitors. Also, the importance of R&D among firms' strategies could be indicated by a larger proportion of the variation in stock market returns "explained" by these

citation measures. It may be possible to empirically support the claim that R&D has become more important to firms' success over time. Finally, another measure of R&D competition would be the time between initial grant and the rent destroying citation. If there has been a trend toward earlier patent citations it would also support the claim that firms' rents are destroyed faster.

There could be citations by the same company. This, I believe will have positive effects on the returns of the company. This also has many implications in terms of the company trying to improve on its previous product or trying to introduce a newer drug that would replace the previous drug and make it harder for competitors to try and produce a competitive drug.

3.3 Model Specification

The estimation strategy combines event study methodology with methodologies currently being developed for patent data. Consider the citations to a firm's patents, $cite_{ijts}$, where i indexes the patenting firm, j indexes the citing firm, t indexes the cited patents grant date and s indexes the citing patent's grant date. Our basic regression equation is,

$$ret_{it} = \alpha_i + \beta_i mktret_t + \phi_i\left(\sum_{\tau=t}^{T} cite_{ijt\tau}\right) + \theta_i\left(\sum_{\sigma=0}^{t} cite_{ij\sigma t}\right) + \varepsilon_{it}$$

where ret_{it} is firm i's stock market return on date t and $mktret_t$ is the aggregate market return on date t. The first summation is the number of future citations from other firms to patents granted on date t. The second summation is the number of citations from

other firms to patents belonging to firm i. The estimate of f_i would be a measure of the importance of positive R&D outcomes on the creation of quasi-rents for a firm. The estimate of q_i would be a measure how much of these rents are destroyed by other firms' future R&D successes.

The basic regression equation could be modified to account for common econometric issues. First, event studies often allow for a multiple day "window" in which the stock price can react to "news." The equivalent here would be to allow for both lag and lead values of the two citation measures. I will be using a one day event, a three day event and a five day event. These windows will be generated for backward citations, forward citations, backward self citations and forward self citations. Second, a null hypothesis might be that the dollar value of a citation to be constant over time. However, using stock market returns implicitly constrains the value of a citation to be proportional to the firm's current market capitalization. The analysis may be hindered if applied to long periods where market capitalization changed dramatically. Third, citations of more recent patents suffer greater truncation due to less elapsed time since grant in which to be cited. The usual corrections is to first estimate citations as a function time with a truncation correction and use the expected number of citations as a regressor (Jaffe, Trajtenberg, 1996).

Policy implications could emerge from comparisons of the estimates of ϕ_i and θ_i and patenting patterns over time and across individual firms. First, larger values of ϕ_i indicate greater importance of R&D outcomes on firm performance. Similarly, larger negative values of θ_i indicate the extent that these new innovations are replaced by

successive innovations by R&D competitors. Second, the importance of R&D among firms' strategies could be indicated by a larger proportion of the variation in stock market returns "explained" by these citation measures. It may be possible to empirically support the claim that R&D has become more important to firms' success over time. Finally, another measure of R&D competition would be the time between initial grant and the rent destroying citation. If there has been a trend toward earlier patent citations it would also support the claim that firms' rents are destroyed faster.

CHAPTER 4

DATA

The data I use in this research comes from three sources: CRSP, data on patents collected by Jaffe and Trajtenberg, and from the FDA website. In this chapter I individually describe how all the datasets were gathered and used for my particular research.

4.1 Data Sources

A Patent gives inventers sole individual rights to sell/market their new invention for a fixed period of time. This ensures that other inventors do not use a similar device for commercial purposes. Usually in the US the length of the patent is 20 years from the filing date. Once a patent is granted in the pharmaceutical industry it does not mean it is ready to be marketed and sold. The drug still has to go through the normal testing procedures before it can even be sold. This means that the patented drug could only be marketed for 10 years if it takes 10 years for FDA to deem the drug as useable by humans. Firms file a written application to the US Patent Office to obtain the patent. The written application explains all the details of the drug such as how to make it, how to use it, and for what purposes is the drug being invented. The patent office will review the application, decide whether it is an innovative creation and give the applicant a chance to defend its stance. Once the patent is granted, firms have to pay a renewal fee every year to keep the patent in force. Since the pharmaceutical industry is one of the

most highly regulated industries therefore drug approvals go under strict scrutiny of the Food & Drug Administration. The drugs go through strict testing and have three phases as explained before to pass before they are eventually approved.

For the bulk of my dataset, I used Patents and Citations Database constructed by Jaffe and Trajtenberg. The database keeps a complete record of citations made by each U.S. patent upon approval since 1963, as well as other patent characteristics such as application date, approval date, and detailed International Patent Classification (IPC) code describing the technological classifications of the patent. It has information on many different industries; however, the research's empirical estimation is based at the moment on pharmaceutical firms publicly traded in the U.S. during 1963 to 1999. It consists of patents granted to innovations made by Pharmaceutical firms. Their database has around 9 million citations made by US patents that are granted by United States Patent Office to previous United States patents. However, after double checking the United States Patent Office website for the citations to the patents in questions, I realized that the Jaffe and Trajtenberg's Patent Database is not up to date in terms of the number of citations. For the purpose of this study, we first identify all the patents owned by each of the Pharmaceutical firm and for each patent we identify the citations made to them. Using those citations I will be able to estimate the sum of forward citations, backward citations and self citations that will help in testing the presence of creative destruction. Using the data available, I cut down my dataset to work with the top pharmaceutical firms in the industry. The research is based on the thirteen firms shown on table 4.1. These thirteen firms have combined to produce many blockbuster drugs

that have been used in USA and they together represent billions of dollars and over 80 percent of pharmaceutical sales.

Table 4.1 Top Pharmaceutical Firms used in the Research

Permno	Cusip	Company Name
19393	11012210	BRISTOL MYERS CO
21936	71708110	PFIZER INC
22111	47816010	JOHNSON & JOHNSON
22752	58933110	MERCK & CO INC
23318	17004010	CHIRON CORP
25013	80660510	SCHERING CORP
26390	83237710	SMITH KLINE & FRENCH LABS
39570	76242T10	RHONE POULENC RORER INC
40010	81230210	SEARLE G D & CO
41937	77070610	ROBINS A H INC
47837	56979010	MARION LABS INC
50876	53245710	LILLY ELI & CO
75064	37733W10	GLAXO HOLDINGS LTD

For individual stock returns and market returns, namely S&P 500 Index, I used the CRSP dataset. The Center for Research in Security Prices (CRSP), based since 1960, maintains the most comprehensive collection of security price, return, and volume data for the NYSE, AMEX and NASDAQ stock markets. CRSP also provides CRSP/COMPUSTAT Merged Database, a database that simplifies matching COMPUSTAT financial data to the CRSP security price data. CRSP maintains historical data sparing from December 1925 to the present and covers roughly 26,500 stocks. CRSP dataset is known to be reliable as all dataset in their database is checked for accuracy and maintains internal consistency. In case of uncertainty for certain values, CRSP has used outside help to ensure the quality of their database. CRSP

created their own unique company identifier called PERMNO such that it could track securities accurately even when company's identifiers such as CUSIP, ticker, company name, SIC code or exchange change. Hence, it is easier to track companies' regardless of mergers and therefore permits accurate observations of returns synchronized with a specific period of time and perform accurate event studies. The CRSP database is updated monthly and offers complete corporate action data for US equities. They offer descriptions of all distributions, dividends amounts, factors to adjust price and shares, declarations, ex-distributions and any other company information. Since the creation of the CRSP database, eighty percent of academic research in stock market and investment analysis have or are still using CRSP datasets as a source due to their completeness and accuracy of information.

The variables used from the CRSP dataset include the daily returns of stocks, daily S&P 500 index, daily value weighted return and the beta excess return. A return is a change in total value of an investment made to a common stock over a period of time per dollar of initial investment. CRSP calculates returns by using the formula:

$$r(t) = [(p(t)f(t)+d(t))/p(t')]-1$$

where,

r(t) = return on purchase at t', sale at t

p(t) = last sale price or closing bid/ask average at time t

d(t) = cash adjustment for t

f(t) = price adjustment factor for t

p(t') = last sale price or closing bid/ask average at time of last available price < t.

Beta Excess Return denotes the excess return of a specific issue less the average return of all issues in its beta portfolio each trading date. Beta measure the risk of a stock in relation to rest of the market. CRSP calculate beta values computed using the methods developed by Scholes and Williams as shown in their paper "Estimating Betas from Non-synchronous Data". Beta's by Scholes and Williams are created using OLS and additional simple linear regressions of R_{jt} on lagged and leading values of R_{mt} and the estimation of the first-order autocorrelation of R_{mt}. R_{jt} is the rate of return of the j^{th} stock on day t and R_{mt} is the rate of return of the CRSP NYSE-AMEX equally weighted market index on day t.

4.2 Data Description

The drug sample from the Jaffe and Trajtenberg's Patent Database was double checked using the historical Orange Book data published by Food & Drug Administration (FDA). The data in the Orange Book describes all patents registered with the FDA that cover new drug applications (NDAs) from 1970 to 2000, including patents issued from 1968-2006. Using the Orange Book, I found all the patents required for every blockbuster drug through the chemical used for producing the drug. By searching the chemical compound in the Orange Book, I find multiple patents cited for that molecule. Usually the oldest patent listed is the first patent for the drug. This helped in trimming through the vast dataset of the Patents and Citations Database. The patent numbers assisted in matching the blockbuster patent to its patent grant date, all citations

to the patent, the citation date, citation assignee, number of citation made by the patent and number of citations received to it. To double check whether I had the right number of citations for my period and patents in question, I checked the United States Patent and Trademark website. Using the patents found from The FDA website, I searched for all the citations to each patent. Each patent document includes the date when the inventor filed for the patent, the patent grant date and all the self citations and citations made by other firms. The United Stated Patent and Trademark website had citations up to 2007, but I limited my dataset up to 1999 to match Jaffe and Trajtenberg's Patents and Citation Database. The Patent and Citation Database had accurate citations for most patented drugs called Lipitor and Zoloft when compared to the United States Patent and Trademark website. However, for other drugs, Jaffe and Trajtenberg's database did not have the right number of citations as per the patent website. For example, for the patented drug called Prilosec, I found no citations in Jaffe and Trajtenberg's database. Using the United States Patent and Trademark website, I found many citations made to the patent of Prilosec up till 1999. The citations to Prilosec are documented in Table 4.2.

Table 4.2 Prilosec's Chemical Patent and Citations up to 1999

Cited	Citing	Date
4786505	4853230	8/1/1989
	5006346	4/1/1991
	5891474	4/6/1991
	5026560	6/25/1991
	5035899	7/30/1991
	5055306	10/8/1991
	5096717	3/17/1992
	5232706	11/3/1992

Table 4.2 - continued

	5160743	4/20/1993
	5204118	7/3/1993
	5356896	10/18/1994
	5433959	7/18/1995
	5472712	12/5/1995
	5580578	12/3/1996
	5622721	4/22/1997
	5639476	6/17/1997
	5639478	6/17/1997
	5651997	7/27/1997
	5681585	10/28/1997
	5690960	11/25/1997
	5788987	8/4/1998
	5817338	10/6/1998
	5824339	10/20/1998
	5840737	11/24/1998
	5880106	3/9/1999
	5879708	3/9/1999
	5731002	3/24/1998

There is a chance that the dataset may run into a truncation problem. This will be a problem especially for forward citations if a blockbuster drug was patented during the last few years of the dataset. The data I have is valid up to December 1999; therefore, if a blockbuster drug is patented after 1996, there is a very small time frame to consider the citations to the patent and their overall effects on the firm's market value. The data limits the number of future citations. This would reduce the number of events and lead to bias results. Usually the bulk of the future citations occur 15 years within the initial patent application. According to Lanjouw and Schankerman (1999), they found some gain but no significance for drugs to extend the citation span beyond five years. Hence, one possible solution is to consider citations to patents that were

granted earlier than 1994. This will provide enough sufficient citations per patent to work with. It could cause a bias but the bias will not be that big to change significance of results. For my research, I cut my patent dataset from 1990 onwards. Hence, I should not have a problem with truncation for forward citations. I also feel that I will not have a truncation problem with backward citations as I have most of the dataset for the early patents. The two main truncation problems are briefly explained further below and if correct measures are taken my results may be more accurate.

The first truncation problems involve patent counts and backward citation counts. The cause for this problem is that there is a time delay in the granting of patents. A possible solution for this will be for me to find the average number of years that takes for patents in the Pharmaceutical industry to be granted. I can then cut the sample period by that average number of years. I am hence able to include most of the granted patents and backward citation counts.

The second truncation problem involves forward citation counts (especially for the most recent patents) and is due to the time lag in observing forward citations. Patents can be cited 10, 20 or even 30 years after its initial application. This limits the forward citations for more current patents compared to patents granted in the 1980s. To address this problem, we estimate a citation-lag model, and then project the number of forward citations each patent would receive for the years not observed in the database.

The above two truncation problems are extreme and may not affect my results. My main concern is the truncation faced by forward citations. My dataset ends in 1999. Therefore, I will not have many years of forward citation counts to work with especially

for those patents granted just before 1999. I have however solved the problem by taking into consideration patents that have been granted before 1990. Hence, this will reduce the bias in my results caused by the truncation. Finally, the dataset I will be working with is summarized in Table 4.2

Table 4.3 Descriptive Statistics of Data

Variable	Mean	Std. Dev.	Min	Max
Price	53.01789	29.89431	-115.5938	217.5
Value Weighted Return	.0004939	.0090773	-.1713528	.0866189
S&P 500 Return	.0004055	.0097799	-.2046693	.0909935
Daily Return	.0008331	.0198956	-.2954545	.509804
Beta Excess Return	.0001016	.0174415	-.2964932	.4926942
Backward Citations	.8780028	3.170144	0	109
Backward Self Citations	.2131725	1.462252	0	55
Forward Citations	.9758711	5.292572	0	234
Forward Self Citations	.2177117	2.106454	0	211

*Observations = 60426

CHAPTER 5

EMPIRICAL RESULTS

This chapter explains the results acquired through the different models used in the research. The table below describes all the different variables used in the research.

Table 5.1 Variable Descriptions

Variable	Description
Return	Daily stock return for each firms
Market Return	Daily S&P 500 return
Backward Citations (Citeb)	Sum of Backward Citations
Forward Citations (Citef)	Sum of Forward Citations
Backward Self Citations (Citebself)	Backward Self Citations
Forward Self Citations (Citefself)	Forward Self Citations
Bxrtn	Beta Excess Returns

Table 5.2 contains the estimates for the effects of the total backward and forward citations on the major pharmaceutical firms overall beta excess returns. The results shown on table look very solid and promising.

Table 5.2 Regression Results

	1	2	3	4	5	6
Backward Citation Lagged Twice						0.0179 (0.0387)
Backward Citation Lagged Once					0.0787** (0.0398)	0.0764*** (0.0402)
Sum of Backward Citations	0.1712* (0.0398)		0.1445* (0.0401)	0.1384* (0.0416)	0.1381* (0.0415)	0.1391* (0.0422)
Backward Citation Lead Once					0.1079** (0.0393)	0.1103*** (0.04)
Backward Citation Lead Twice						0.0305 (0.038)
Forward Citation Lagged Twice						0.0232** (0.0104)
Forward Citation Lagged Once					0.0274** (0.0102)	0.0268*** (0.0102)
Sum of Forward Citations		0.0447* (0.0093)	0.0374* (0.0095)	0.0307** (0.0104)	0.0295** (0.0104)	0.03** (0.0104)
Forward Citation Lead Once					0.0173*** (0.0105)	0.0183*** (0.0105)
Forward Citation Lead Twice						0.0191*** (0.0105)
Backward Self Citation Lagged Twice						0.0395 (0.0532)
Backward Self Citation Lagged Once					-0.0048 (0.0558)	0.0046 (0.0558)
Sum of Backward Self Citations				-0.0096 (0.0546)	-0.0051 (0.0547)	0.0051 (0.0548)
Backward Self Citation Lead Once					0.0687 (0.0512)	0.069 (0.0513)
Backward Self Citation Lead Twice						0.0442 (0.0511)
Forward Self Citation Lagged Twice						0.0129 (0.0251)
Forward Self Citation Lagged Once					-1.00E-04 (0.02412)	0.0002 (0.0242)
Sum of Forward Self Citations				0.0522** (0.0234)	0.0543** (0.0235)	0.0542** (0.0235)
Forward Self Citation Lead Once					-0.0154 (0.0187)	0.016 (0.0186)
Forward Self Citation Lead Twice						0.0406*** (0.022)
Observations	60426	60426	60426	60426	60425	60424
R-Squared (Within)	0.0029	0.0029	0.0031	0.0031	0.0035	0.0036

Standard Errors in Parentheses
***significant at 10%; **significant at 5%; *significant at 1%
All co-efficient are multiples of 1000.

The above results were estimated by regressing the beta excess returns to backward citations, three day windows of backward citations, five day windows of backward citations, backward self citations, three day window for backward self citations, five day window for backward self citations, forward citations, three day window of forward citations, five day window of forward citations, forward self citations, three day window of self citations and five day window of self citations. The results show that citations to patents have a significant effect on the market value of the firms.

In table 5.2, column 1 shows the regression results for the effects of backward citations on the beta excess returns. The coefficient indicates that when a citing firm's patent is granted, the citation made by the citing patent to the cited patents has positive effects to the market value of the assignee of the cited patent. The coefficient shows that a citation to the cited firm increases the market value of the cited firm 0.00071%.

Column (2) from table 5.2 shows the regression results for the effects of forward citations on beta excess returns. The results show that the forward citations have a positively correlated to the returns of the cited firms. The significance of the coefficient indicates that when the cited patent is granted, the greater number of citations it receives in the future, the cited firm's market value is more than likely to rise. The coefficient shows that a future citation to the cited firm increases the market vale of the cited firm by 0.000045%.

Column (3) from table 5.2 shows the regression results for the effects of both backward and forward citations on the beta excess returns of the pharmaceutical firms. The coefficients indicate that a forward citation increases cited firm's market value holding backward citation constant. Likewise, the coefficient of backward citation indicates that a backward citation increases a cited firm's market value holding forward citations constant. Both coefficients are significant at the 1% level. The coefficient for backward citation shows that a citation to the cited firm increases the market value of the cited firm by 0.000138%. The coefficient for forward citation shows that a future citation to the cited firm will raise the market vale of the cited firm by 0.000037%.

Column (4) form table 5.2 shows the regression results for the effects of backward citation, forward citation, backward self citation and forward self citation on each firm's beta excess returns. The coefficient for backward citation is positively significant at the 1% level. The coefficient for forward citation is positively significant at the 5% level. The coefficient for forward self citation is also positively significant at the 5% level. However, the coefficient for backward self citation is insignificant. The coefficient for backward citation shows that a citation to the cited firm increases the market value of the cited firm by 0.000145%. The coefficient for forward citation shows that a future citation to the cited firm will raise the market vale of the cited firm by 0.000031%. The coefficient for forward self citation shows that when a firm cites to itself sometime in the future it will raise the market vale of the firm by 0.000052%. My results show that backward self citation has no effect on the cited firm. The

insignificance of the backward self citation could change when we look at the different windows.

Column (5) form table 5.2 show the regression results for the effects of three day backward citation window, three day forward citation window, three day backward self citation window and three day forward self citation window. The coefficients for one lagged backward citation, backward citation and one lead backward citation are all positive and significant. The coefficient of backward citation is significant at the 1% level. The coefficients for one lagged forward citation, forward citation and one lead forward citation are also all positive and significant. The coefficients for one lagged backward self citation, backward self citation and one lead backward self citation are all insignificant. The coefficient for forward self citation is all positive and significant at the 5% level. However, the coefficients of one lagged forward self citation and one lead forward self citation are both insignificant. Table 5.3 has results for linear combinations of the three day windows for all variables. As expected, the combination of the three day events for backward and forward citations has significant results. However, results for the backward self citation and forward self citations are insignificant.

Column (6) form table 5.2 show the regression results for the effects of five day backward citation window, five day forward citation window, five day backward self citation window, forward self citation, five day forward self citation window. The coefficients for one lagged backward citation, backward citation and one lead backward citation are all positive and significant. However, the coefficients for two lagged

backward citation and two lead backward citations were insignificant. The coefficients of the five day window for forward citations are all positive and significant. The coefficients for the five day window for backward self citation are all insignificant. The coefficient for forward self citation and second lead window is positive and significant at the 5% and 10 %, respectively. However, the coefficients of two lagged forward self citation, one lagged forward self citation and one lead forward self citation is insignificant. Table 5.3 has results for linear combinations of the five day windows for all variables. As expected, the combination of the three day events for backward and forward citations has significant results. However, results for the backward self citation and forward self citations are insignificant. This shows that the regression results are not spurious. This shows that all the information concerning any citation has been captured within the five day windows and therefore proves that the returns do react to the news of citations and that no information of the citations has been left out.

Table 5.3 Linear Combinations of Estimators at different windows

	One Day Window	Three Day Window	Five Day Window
Backward Citations	0.1384* (.0416)	0.3247* (.0718)	0.3384* (.1017)
Forward Citations	0.0307* (.0104)	0.0743* (.0179)	0.0788* (.024)
Backward Self Citations	-0.0096 (.0546)	0.0588 (.0953)	0.0639 (.1241)
Forward Self Citations	0.0521** (.0234)	0.0388 (.0389)	0.0103 (.0513)

Standard Errors in Parentheses
***significant at 10%; **significant at 5%; *significant at 1%
All co-efficient are multiples of 1000.

CHAPTER 6

CONCLUSIONS

In summary, the results illustrate that the forward and backward citations have a positive effect to the returns of the assignee of the cited patents. Forward citations occur on the date that the cited patent is granted and refers to the number of citations a patent will eventually receive. If a cited patent receives several future citations, it shows the importance of the patent or drug. According to my results, if a patent is cited more than other patents, the frequently cited patent has a larger effect on the stock market. Backward cites occur on the date that the citing patent is granted and refers to the number of patents on that date it cites to any patent held by the assignee of the cited patent. Creative destruction suggests that backward citations should destroy rents of the cited firms. However, my results suggests otherwise. The regression results demonstrate that Schumpeterian explanation of capitalism's creativity ability prevails over the destructions process. One possible reason for backward citations to have a positive impact on the market value could be that the importance of the cited patents does in fact over weigh the benefit of the new technology being introduced. Furthermore, the original or cited firm can protect its market through follow on patenting thus reducing the effect of destruction element of citations. Firms continue spending billions of dollars on Research and Development to further improve their own patents so as to make it difficult for competitors to imitate old patents.

The results also showed that forward self citations had positive and significant results. This indicates greater importance of R&D outcomes on firm strategy. My results showed that if a firm has extensive R&D program and looks to build over past own patents, it increases market value. R&D becomes particularly more important to a cited firm when other patents frequently cite to its patent. A cited patent will want to continue extensive R&D so as to avoid new technologies from stealing its market share. Overall, the research finds that a firm's creativity and R&D outcomes will eventually cause firm's market value to increase.

APPENDIX A

ECONOMETRIC RESULTS

Table A.1: Regression results using daily returns

	1	2	3	4	5	6
Backward Citation Lagged Twice						4.22e-03 (0.0337)
Backward Citation Lagged Once					0.0269 (0.0337)	0.0284 (0.0341)
Sum of Backward Citations	0.076** (0.0318)		0.0618*** (0.0324)	0.0558*** (0.0334)	0.0552 (0.0334)	0.0599 (0.0399)
Backward Citation Lead Once					0.0334 (0.0333)	0.0383 (0.0337)
Backward Citation Lead Twice						-0.0526 (0.0336)
Forward Citation Lagged Twice						0.0195** (9.34e-03)
Forward Citation Lagged Once					0.0167*** (9.2e-03)	0.0165 (9.23e-03)
Sum of Forward Citations		0.0229** (8.2e-03)	0.0198** (8.4e-03)	0.0132 (9.2e-03)	0.0127 (9.19e-03)	0.0132 (9.21e-03)
Forward Citation Lead Once					8.5e-03 (9.4e-03)	9.39e-03 (9.42e-03)
Forward Citation Lead Twice						-0.0135 (9.66e-03)
Backward Self Citation Lagged Twice						-0.0526 (0.049)
Backward Self Citation Lagged Once					9.03e-03 (0.0495)	-7.16e-03 (0.0495)
Sum of Backward Self Citations				-8.84e-03 (0.0483)	6.97e-03 (0.0483)	-4.74e-03 (0.0484)
Backward Self Citation Lead Once					0.0564 (0.046)	0.0585 (0.0461)
Backward Self Citation Lead Twice						0.0513 (0.0468)
Forward Self Citation Lagged Twice						0.0262 (0.0264)
Forward Self Citation Lagged Once					-3.8E-03 (0.0224)	-3.44e-03 (0.0224)
Sum of Forward Self Citations				0.0514** (0.0219)	0.0523** (0.0219)	0.0525 (0.0219)
Forward Self Citation Lead Once					-0.046 (0.0176)	-0.0146 (0.0176)
Forward Self Citation Lead Twice						-0.0292 (0.0214)
Observations	65836	65836	65836	65836	65836	65834
R-Squared (Within)	0.24	0.24	0.24	0.24	0.24	0.24

Standard Errors in Parentheses
***significant at 10%; **significant at 5%; *significant at 1%
All co-efficient are multiplied by a 1000.

Table A.2: Linear Combinations of Estimators using Daily Returns

	One Day Window	Three Day Window	Five Day Window
Backward Citations	0.0558*** (0.0334)	0.1154*** (0.0599)	0.1684*** (0.0863)
Forward Citations	0.0132 (9.2e-03)	0.0378** (0.0161)	0.05** (0.0217)
Backward Self Citations	-8.84e-03 (0.0483)	0.0339 (0.0362)	0.0453 (0.1119)
Forward Self Citations	0.0514** (0.0219)	0.0404 (0.0848)	0.0316 (0.0498)

Standard Errors in Parentheses
***significant at 10%; **significant at 5%; *significant at 1%
All co-efficient are multiplied by a 1000.

APPENDIX B

CITATIONS

Table B Pfizer Forward Citations

Firm	Drug	Cited Patent	Citing Patent	Date	Forward Citations	Forward Self Citation
Pfizer	Lipitor	4572909	4672071	6/9/1987	1	0
			4694012	9/15/1987	1	0
			4870091	9/26/1989	1	0
			4971984	11/20/1990	1	0
			5026863	6/25/1991	1	0
			5039679	8/13/1991	1	0
			5110820	5/5/1992	1	0
			5196410	3/23/1993	0	1
			5234943	8/10/1993	1	0
			5270323	12/14/1993	0	1
			5389654	2/14/1995	1	0
			5391548	2/21/1995	0	1
			5438145	8/1/1995	1	0
			5639777	6/17/1997	0	1
			5700816	12/23/1997	1	0
			5723618	3/3/1998	0	1
			5756529	5/26/1998	0	1
			5892053	4/6/1999	0	1
			5908852	6/1/1999	0	1
			5910597	6/8/1999	0	1
			5972986	10/26/1999	0	1
			5990148	11/23/1999	0	1
	Zoloft	4536518	4777288	10/11/1988	1	0
			4839104	6/13/1989	1	0
			4855500	7/8/1989	1	0
			4940731	7/10/1990	1	0
			4962128	10/9/1990	1	0
			5082970	1/21/1992	1	0
			5091429	2/25/1992	0	1
			5130338	7/14/1992	1	0
			5196607	3/23/1993	1	0
			5248699	9/28/1993	1	0
			5288916	2/22/1994	0	1
			5442116	8/15/1995	1	0
			5463126	10/31/1995	1	0
			5734083	3/31/1998	0	1
			5750794	5/12/1998	1	0

Table B - continued

Firm	Drug	Cited Patent	Citing Patent	Date	Forward Citations	Forward Self Citation
	Celebrex	5466823	5639777	6/17/1997	0	1
			5700816	12/23/1997	1	0
			5756529	5/26/1998	0	1
			5892053	4/6/1999	0	1
			5908852	6/1/1999	0	1
			5910597	6/8/1999	0	1
			5972986	10/26/1999	0	1
			5990148	11/23/1999	0	1
	Neurontin	4894476	5068413	11/26/1991	1	0
		4894476	5091567	2/25/1992	1	0
	Viagra	5250534	5426107	6/20/1995	0	1
			5602140	2/11/1997	1	0

APPENDIX C

CITATION STATISTICS

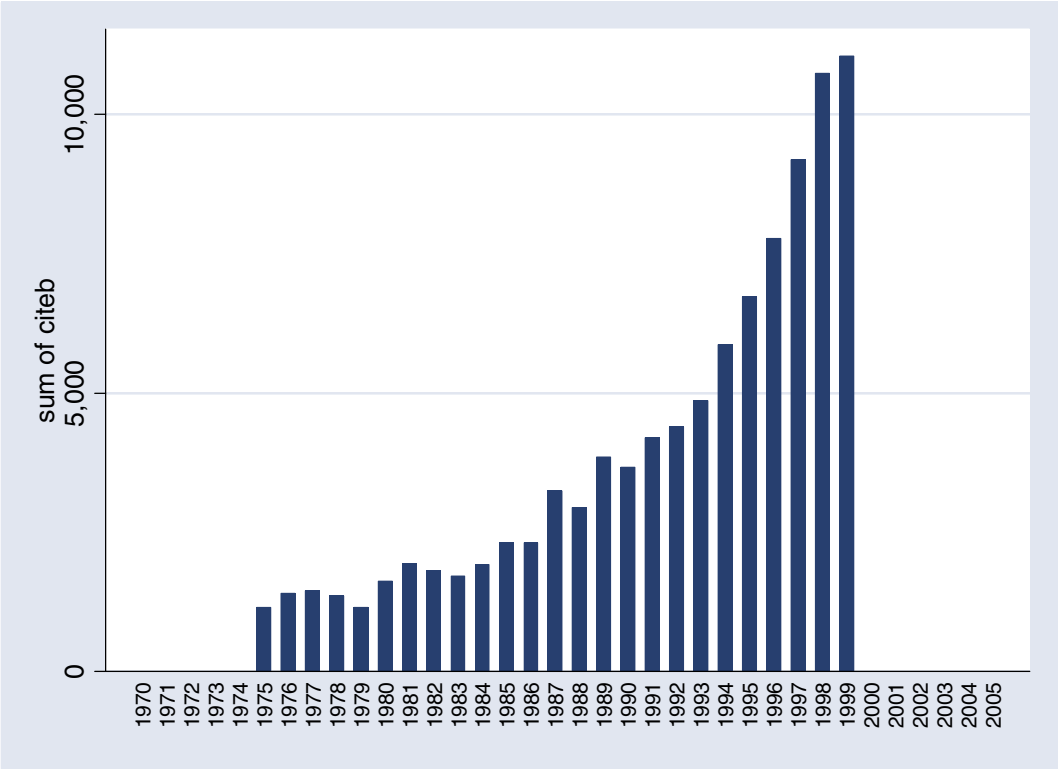

Diagram 1 Histogram of Sum of Backward Citations

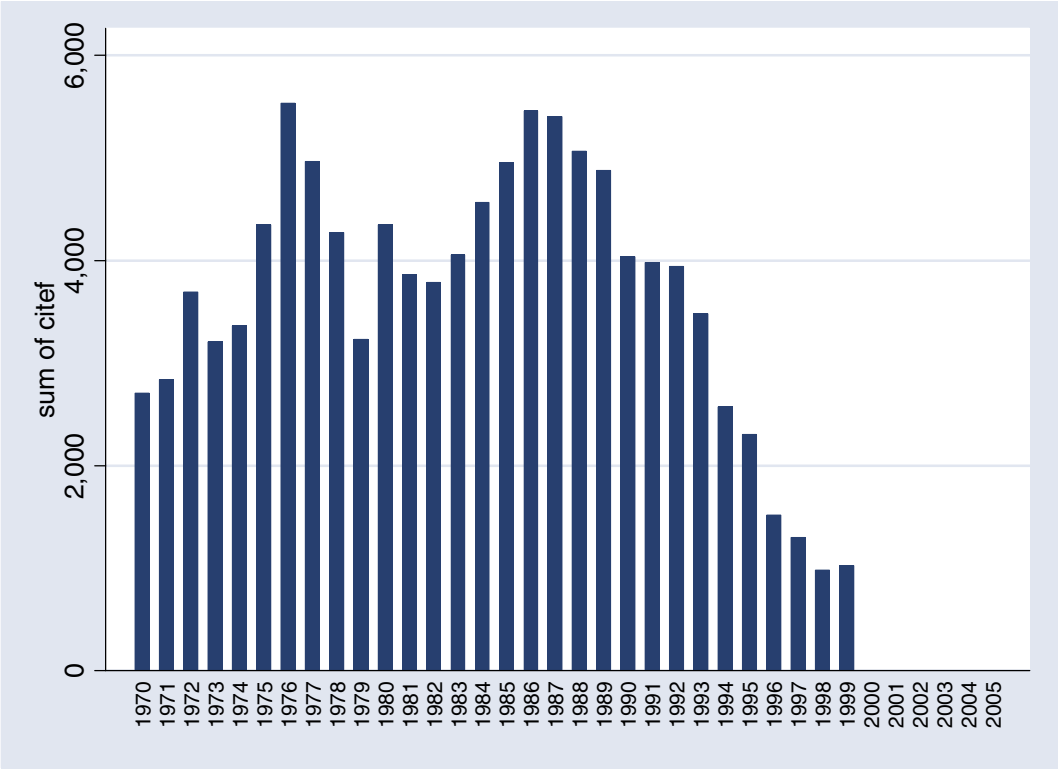

Diagram 2 Histogram of Sum of Forward Citations

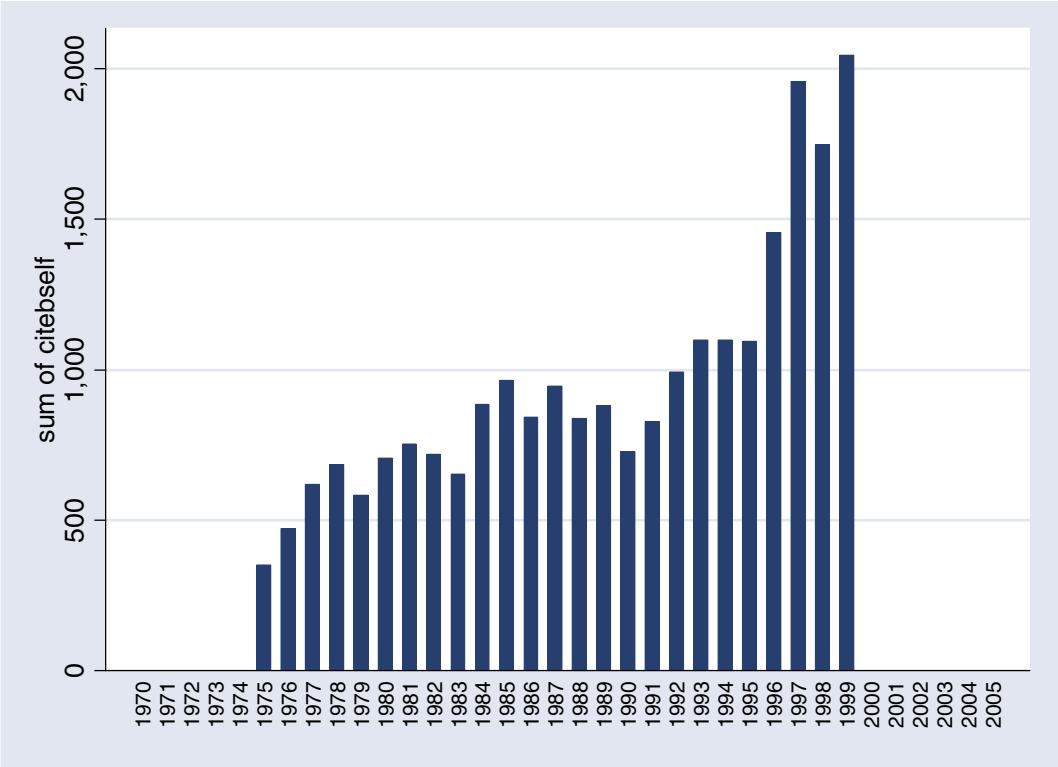

Diagram 3 Histogram of Sum of Backward Self Citations

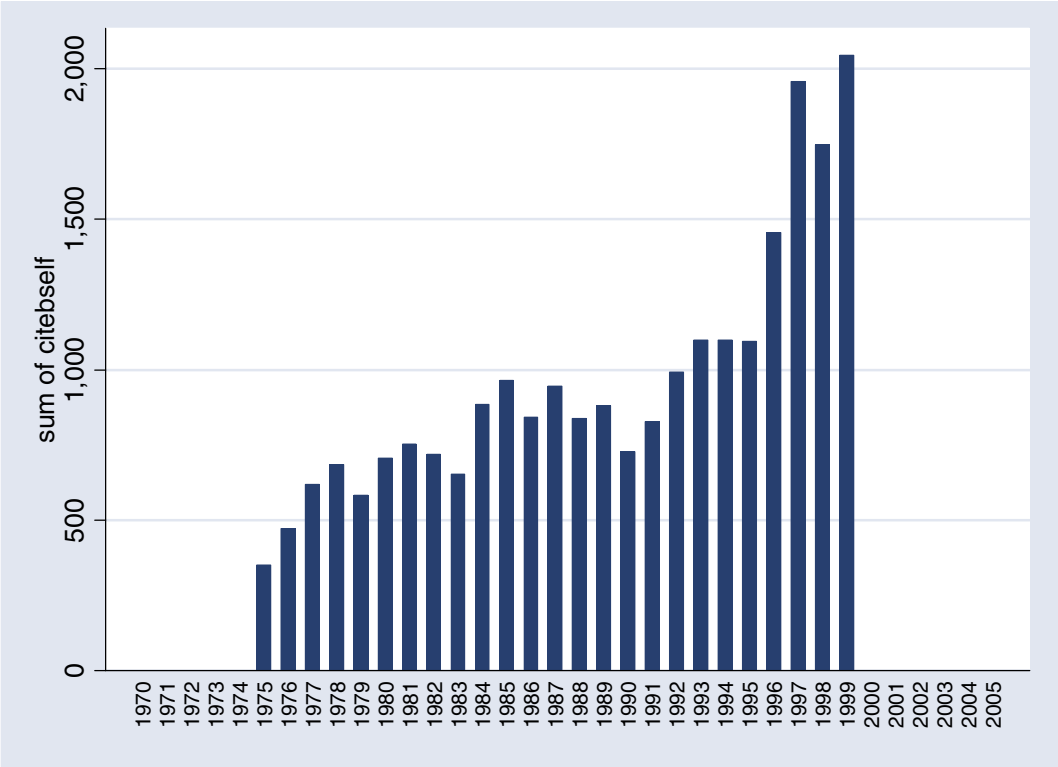

Diagram 4 Histogram Sum of Forward Self Citation

REFERENCES

Baily, Martin (1972). Research and Development Costs and Returns: The U.S Pharmaceutical Industry. Journal of Political Economy, 80(1), 70-85.

Bitzer, Jurgen (2005). Measuring Knowledge Stocks: A Process of Creative Destruction. Kyklos, 58, 379-393.

Comanor, William (1964). Research and Competitive Product Differentiation in the Pharmaceutical Industry in the United States. Economica, 31, 372-384

Deng, Yi (2006). The Value of Knowledge Spillovers in the U.S. Semiconductor Industry

Dranove, David & Meltzer, David (1994). Do Important Drugs Reach the Market Sooner? RAND Journal of Economics, 25 (3), 402-423.

Grabowski, Henry & Vernon, John (1990). A new Look at the Returns and Risks to Pharmaceutical R&D. Management Science, 36 (7), 804-821.

Griliches, Zvi (1981). Market Value, R&D, and Patents. Economic Letters, 7, 183-187.

— (ed.) (1984). R&D, Patents and Productivity. University of Chicago Press, Chicago.

—, (1990). Patent Statistics as Economic Indicators: A Survey. Journal of Economic Literature, XXVIII, 1661-1707.

— and J. A. Hausman (1986). Errors in Variables in Panel Data. Journal of Econometrics, 31, 93-118.

Grossman, Gene and Elhanan Helpman (1991). Quality Ladders and Product Cycles. Quarterly Journal of Economics, 106, 557-586.

Hall, Bronwyn H., (1990). The Manufacturing Sector Master File: 1959-1987. NBER Working Paper No. 3366.

Henderon Jr, Glenn (1990). Problems and Solutions in Conducting Event Studies. Journal of Risk and Insurance, 57, 282-306.

—, Adam B. Jaffe, and Manuel Trajtenberg (2001). The NBER Patent Citations Data File: Lessons, Insights and Methodological Tools. NBER working paper No. 8498. Reprinted as Chapter 13 in Jaffe and Trajtenberg (2002).

—, —, and Manuel Trajtenberg (2005). Market Value and Patent Citations. Rand Journal of Economics,36(1).

— and Rosemarie Ham Ziedonis (2001). The Patent Paradox Revisited: An Empirical Study of Patenting in the U.S. Semiconductor Industry, 1979-1995. Rand Journal of Economics, 32 (1), 101-128.

Harhoff, Dietmar, Francis Narin, F.M. Scherer and Katrin Vopel (1999). Citation Frequency and the Value of Patented Inventions. The Review of Economics and Statistics, 81(3), 511-515.

Jaffe, Adam and Joshua Lerner (2001). Reinventing Public R&D: Patent Policy and the Commercialization of National Laboratory Technologies. Rand Journal of Economics, vol. 32 (1), 167-199.

Johnson, Lewis, and Bohumir Pazderka, (1993). Firm Value and Investment in R&D. Managerial and Decision Economics, 14, 15-24.

— and — (2002). Patents, Citations and Innovations: A Window on the Knowledge Economy. Cambridge: MIT Press.

—, —, and Michael Fogarty (2000). The Meaning of Patent Citations: Report of the NBER/Case Western Reserve Survey of Patentees. NBER working paper No. 7631.

—, —, and Henderson, Rebecca (1993). Geographic Location of Knowledge Spillovers as Evidenced by Patent Citations. Quarterly Journal of Economics, 108, 577-598.

Lanjouw, Jean O. and Schankerman, Mark A. (1999). The Quality of Ideas: Measuring Innovation with Multiple Indicators. NBER Working Paper No. W7345.

MacKinlay, A. Craig (1997). Event Studies in Economics and Finance. Journal of Economic Literature, 35, 13-39.

Nicholas, Tom (1993). Why Schumpeter Was Right: Innovation, Market Power and Creative Destruction in 1920s America. Journal of Economic History.

Pakes, Ariel (1985). On Patents, R&D, and the Stock Market Rate of Return. Journal of Political Economy, 93, 330-409.

Romer, Paul (1990). Endogenous Technological Change. Journal of Political Economy, 98, 71-102.

Salinger, Michael (1992). Value Event Studies. Review of Economics and Statisitics, 74, 671-677.

Scherer, F.M (1993). Pricing, Profits, and Technological Progress in the Pharmaceutical Industry. Journal of Economic Perspectives, 7 (3), 97-115.

Scherer, F.M. (1965). Firm Size, Market Structure, Opportunity, and the Output of Patented Innovations. American Economic Review, 55, 1097-1123.

Scotchmer, Suzanne (1991). Standing on the Shoulders of Giants: Cumulative Innovation and the Patent. Journal of Economic Perspectives, 5, 29-41.

Teeling-Smith, George (1980). Economic Misconceptions in the Pharmaceutical Industry. Managerial and Decision Economics, 1, 37-41.

Temin, Peter (1979). Technology, Regulation, and Market Structure in the Modern Pharmaceutical Industry. Bell Journal of Economics, 10 (2), 429-446.

Virts, John and Weston, J. Fred (1980). Returns to Research and Development in the US Pharmaceutical Industry. Managerial and Decisions Economics, 1 (3), 103-1

BIOGRAPHICAL INFORMATION

Darshak Patel received a Bachelor of Science in Economics from University of Texas at Arlington in December 2004. With the completion of this research, Darshak will be able to graduate with his Masters of Arts in Economics from UTA in May 2007. He hopes to have completed his PhD in Economics by May 2011.