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Essays on Patent Transfer Behavior in The Pharmaceutical Industry

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Abstract of the Dissertation

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While large pharmaceutical companies continue to dominate drug development and patent acquisition, their timing of drug patent acquisition and subsequent payoffs remain poorly understood. In an effort to examine the patent acquisition timing in the U.S. pharmaceutical industry, both empirical and theoretical approaches are used to analyze the effects of firm characteristics on the timing of patent purchases. In Chapter 1, I construct a unique dataset using publicly-available data provided by the United States Patent and Trademark Office (USPTO), and examine the purchasing behavior of public firms within the U.S. pharmaceutical industry. I focus on the role of firm size and composition in affecting the timing of patent purchases and the subsequent payoff; particularly, how firms R&D intensity and overall scale affect purchasing decisions and commercial success of the drugs. The quantitative results show that, on average, firms with larger scale and stronger R&D departments are more likely to purchase drug patents later; furthermore, a strong R&D department contributes positively to drug sales and market shares through a better selection process of patents. The economics intuition is that firms with a larger scale and greater emphasis on R&D investment have advantages in producing in-house innovation, so they tend to be more selective when buying from outsources. This results purchasing

patents later in the drug development process and better subsequent performance of the drug patents they do purchase.

In Chapter 2, which serves as the theoretical framework for the first chapter, I explore the incentives of drug firms in strategically selecting the purchasing time for outsourced drug patents. According to the theoretical framework, each drug patent has to pass n testing phases before its approval, and the buyer firm can choose to acquire patents at any stage (with k stages left) and pay a market price that is a function of the number of phases left. Overall trial cost for each drug project is a function of k. After purchase, the buyer firm needs to finish the remaining phases in order to make the drug patent marketable. Firms are heterogeneous in trial success rates, and choose their optimal timing of acquisition to maximize profit. The results show that the number of remaining stages (when patent is purchased) is a decreasing function of trial success rate. In other words, firms with better expertise benefit from delaying patent purchases.

Frontispiece

The frontispiece is generally an illustration, and is an optional page.

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Thank you very much, everyone!

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Stony Brook, August, 2017.

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- "Aortic Valve Disease with Ascending Aortic Aneurysm: Impact of Concomitant Root-sparing (supracoronary) Aortic Replacement in Non-syndromic Patients," with Sven Peterss, et al., *J Thorac Cardiovasc Surg. 2016; 152: 791-798.*

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Timing and Payoff of Patent Purchases: the Role of Firm Size and Composition

Yupeng Li

August 12, 2017

Abstract

While large pharmaceutical companies continue to dominate drug development and patent acquisition, their timing of drug patent acquisition and subsequent payoffs remain poorly understood. In an effort to examine the patent acquisition timing in the U.S. pharmaceutical industry, both empirical and theoretical approaches are used to analyze the effects of firm characteristics on the timing of patent purchases. In Chapter 1, I construct a unique dataset using publicly-available data provided by the United States Patent and Trademark Office (USPTO), and examine the purchasing behavior of public firms within the U.S. pharmaceutical industry. I focus on the role of firm size and composition in affecting the timing of patent purchases and the subsequent payoff; particularly, how firms R&D intensity and overall scale affect purchasing decisions and commercial success of the drugs. The quantitative results show that, on average, firms with larger scale and stronger R&D departments are more likely to purchase drug patents later; furthermore, a strong R&D department contributes positively to drug sales and market shares through a better selection process of patents. The economics intuition is that firms with a larger scale and greater emphasis on R&D investment have advantages in producing in-house innovation, so they tend to be more selective when buying from outsources. This results purchasing patents later in the drug development process and better subsequent performance of the drug patents they do purchase.

Introduction

The pharmaceutical industry is highly research intensive. And despite its riskiness, it is a lucrative industry, giving firms the incentive to spend billions of dollars on developing and marketing their drug products. Quite commonly, drug patents are purchased from other companies. This may occur both prior to drug approval and after the drug is already on the market. Whether or not a drug will achieve commercial success depends upon the firm's knowledge and marketing expertise. Previous work has captured this under the umbrella of firm size. Yet R&D effort and marketing are two distinct activities. The first is related to drug quality, while the latter is related to consumers' beliefs about the drug's safety and efficacy. In this paper, these two effects are addressed by the size of the R&D department and marketing department, which are respectively measured by R&D expenditures and marketing expenditures. How each of these sectors affect the purchasing timing and success of drugs is examined.

Marketing promotes drug sales differently as R&D efforts proceed. A firm can focus more on drug development by spending more on R&D activities and thus hoping to increase the chance of having higher quality products and, in turn, greater revenues. On the other hand, by spending more money on advertisements and promotion activities, a firm may establish brand loyalty with consumers, which enhances drug sales. However, in both cases, more spending may not guarantee higher revenue. The reason is that the real quality of the drug in actual use is only determined over time as the drug is used. This paper links the different performances (namely sales and market shares) of drugs to firm sizes, where sizes refers to a firm's overall resources in two dimensions, both scale and compositions. This paper also assumes that within a pharmaceutical firm, there are two departments: the R&D department, where the research experts are working, and a marketing department, where advertising, administration and sales promotion occurs[1]. Both divisions rely heavily on the firm's current period revenue, with the larger department having greater influence in the firm's decision on the timing of patent purchases. These two departments have different objectives. The R&D department is rewarded by the approval rate of drug portfolios. The marketing department is rewarded by number of drugs it promotes and

[1]Aggregation both division expenditure take more than 60% of overall revenue on average.

total sales revenues. The R&D department prefers patents with a higher probability of becoming approved drugs, so they are cautious when buying patents and would prefer to buy at a later and thus safer stage. At the same time, the marketing department would prefer to have as many potential drugs as possible, which give them incentives to support early purchases.

There are two major study objectives of this paper. First, how does firm department scale and composition affect the timing of patent purchasing behavior in the pharmaceutical industry? Second, what is the effect of firm scale and composition on the sub-sequent commercial success of the drugs? More specifically, will patents purchased earlier in the drug development process (which would also be more risky) turn out to generate more or less revenue for the buyer firms? In addressing each of these questions, I will measure firm composition separately in terms of R&D and marketing expenditures.

In this research, I used the top selling prescription drugs [2] from the years 2003 to 2013. According to the annual national prescription drug expenditures in the US (CMS Household Survey data), these drug sales account for more than 60% of all prescription expenditures. So this sample is representative of the majority of drug sales in the United States within a given period. Total annual sales will be used to measure the commercial success of a drug.

Obtaining data on outsourcing of drugs is challenging, both because such data are proprietary and very costly to obtain, if available at all. Hence the literature on this topic is quite limited. The present study uses a novel approach to obtain such information from publicly available data. More specifically, I use patent data from United States Patent and Trademark Office (USPTO). Since firms can use drug patent assignment to guarantee drug ownership, I use drug patents transfer data to capture the transfer of drugs. The patent owner retains market exclusivity in exchange for the public disclosure and accessibility of the invention after a defined time period.[3].

One certain drug trade name can be linked to one or more patents associated with the drug. If the drug is acquired by any other firm from its current owner, the patent ownership would go along with the drug ownership. Figueroa and Serrano (2013) describe the trend of patent flow and find that for most industries, larger firms are more selective in patent purchasing, in the sense that the patent they purchased has a lower probability of being

[2]Due to availability of data collected. Top 200 drugs from 2003-2010 and top 100 drugs from 2011 to 2013.

[3]Normally 20 years and can be extended due to different situations. For example, if it is an orphan drug, it would have a 12 year extension to remain market exclusivity.

terminated [4].

Unlike other kinds of intellectual property, in the world of patents, the terminology for ownership is *patent assignment*. When a patent changed its owner, the patent assignment is claimed to have changed. This paper thus uses changes in patent assignments as the indicator of the related drug ownership change. [5]The USPTO patent assignment data documents each patent transfer. And using the FDA database [6], I am able to identify the date of approval for each drug name. The time difference between drug patent transfer and the drug approval date allows one to identify if the patent was transferred before or after FDA approval, and how early prior to approval, or how late after approval.[7]

Most studies have simply examined the effect of total firm size on economic performance; for instance, effects of total firm assets on product return, or R&D expenditure alone on the product return. In contrast, this paper decomposes firm's scale into two components– marketing and research intensity. Therefore the effects of different firm scale factors are examined, measured by annual marketing and R&D expenditure, using the COMPUSTAT Database, on the timing of patent purchase and subsequent commercial success. Due to data availability and characteristics of the COMPUSTAT database, the target firms are all publicly-traded firms. Thus, this study does not consider, for example, differences in patent purchasing behavior between Pfizer and small start-ups, but rather, different purchasing behavior within well-established publicly-traded firms. Nonetheless, the firms in my sample differ substantially in terms of size – some firms may spend as little as a few million dollars on marketing and R&D, while others spend billions. Hence, there is considerable variation in both R&D and marketing effort.

Since I don't directly observe the actual patent purchase price, I follow Chen, Hong, Huang, and Kubik (2004) in constructing a proxy measure. Chen et al. examine whether mutual fund size erodes fund performance.

[4]If the patent owners do not pay for the patents renewal fee and maintenance fee, the patents would expire, or be terminated

[5]Licensing behaviors in which the user-ship of the patent is assigned to other companies while the ownership never changes are not observed. It could be the case that for some drugs, the actual seller is different from the drug patent owner, and such scenario would be discussed if licensing data are available. At this point, I need to assume such behavior is not a common case as sellers would prefer a hostile takeover if the drug is really profitable and would stop marketing the drug if it has a bad demand.

[6]Orange Book

[7]most patents are applied after animal tests are conducted

They use the seller's characteristics to construct a measure of mutual fun size. Following their approach, I determine whether the patents are purchased from a small seller or a large one. I define small sellers if the assignors of patents are groups of individuals, and big seller if assignors are documented corporations. If the seller groups are small, it seems quite likely that the buyer firm wants to buy a less costly patent[8]. Such seller characteristics can help reveal the characteristics of the purchase deal. Since the actual transaction prices of patent transfers are typically unavailable (handbook of IO), this approach provides some insight into the likely magnitude of the transaction price.

The empirical results suggest that larger R&D divisions delay patent purchasing, while firms with larger marketing departments engage in earlier patent purchases. Further, stronger marketing departments enhance drug sales, controlling for firm and drug characteristics, but their influence on earlier purchases of patents appears to have the opposite effect. In contrast, firms with larger R&D departments, though not contributing directly to the drug sales process, may enhance commercial success by choosing patents more conservatively and later in the drug development process – patents that are more likely to produce drugs that are approved and achieve commercial success.

This research makes a number of contributions: first, I employ USTPO data in a novel way to capture historical drug ownership changes. Second, the study employs two dimensions of firm overall resources (R&D and marketing expenditures) to assess their relative success in acquiring and achieving commercially successful drugs. Third, I carefully document the patent transfer time difference within the pharmaceutical industry between differently-sized firm. Fourth, I measure the commercial performance of patents using actual drug sales. Finally, the study provides evidence on asymmetric information between different buyers in the drug patent market.

The paper proceeds as follows. Section 1 provides the review of the relevant literature. In section 2 I describe the data source and statistical details of the database. Study methods and empirical results are presented in Section 3. Section 4 summarizes the results and their implications.

[8]according to bargaining power, small start-ups are easier to be dealt with, so buying from start-up would be cheaper than from a well established firm.

1 Literature Review

Discussions of firm's different performance due to size dates back to the Schumpeterian's hypothesis on economies of scale, which explains the productivity advantages that large firms enjoy. There is a substantial literature examining research and development on different measures of productivity, for instance the number of innovations produced, profits generated and revenue size. Due to the availability of data, this paper focuses on revenues as measurement of final productivity.

A study by DiMasi, Grabowski, and Vernon (1995) is relevant to the present analysis. They found that sales per new drug approved increased markedly with firm size. The results are consistent with substantial economies of scale in pharmaceutical R& D. In a subsequent paper, DiMasi (2014), evaluates R&D performance by firm size in the pharmaceutical industry using data from 2009. Performance is measured in terms of approval rates as well as economic returns, the latter measured by each drug's sales. He finds that larger firms tend to have higher mean sales. In contrast to Dimasi (2014), this paper considers a panel of drug sales from 2003 to 2013, as well as examining the separate roles of R&D and marketing in the timing and success of patent purchases.

There is a considerable literature in finance on how R&D or marketing (advertising) spending affects firm performance, such as revenue (Dekimpe and Hanssens, 1999) (Morbey and Reithner, 1987), and productivity (Levin and Reiss, 1988). But there is very little research on how each division has affected these outcomes within the same study. Thus there is little reliable evidence on the relative importance of each division in affecting a firm's performance.

Higgins and Rodriguez (2006) examines pharmaceutical acquisitions from 1994-2001 and find evidence that on average acquirers realize significant positive returns. For acquisitions characterized by information asymmetries, the evidence is consistent with the proposition that acquirers are able to avoid the winner's curse. They find that experience in sales and drug development pipelines play important roles in a firm's return and their acquisition decision. Here the drug pipeline is a portfolio of chemical compounds under development before FDA approval, some are in phase 1, some in phase 2 and phase 3, etc. When the two factors are taken into account together, sales experience has a positive and significant effect on sales while pipeline experience has mixed results. This paper explicitly examines these two fea-

tures separately to measure their relative impact on sales. Since ultimately both divisions promote revenue through different channels, it is important to examine the contribution of each. This, in turn has implications for the optimal allocation of funds between the two divisions.

Some major advantages of firms with larger scale (or disadvantage of small scale firms) are expertise or experience in the field, public connections, less liquidity restrictions etc.. Hall, Jaffe, and Trajtenberg (2001) concluded that small and new innovative firms experience high costs of capital and even large firms prefer internal funds for the financing of R&D. Pisano (2006) notes that new bio-tech firms are financially constrained and a few unsuccessful drug candidates can lead to bankruptcy.

Danzon, Nicholson, and Pereira (2005) examine success rates in phases across different drug therapeutic categories. They find that the returns to experience are statistically significant in trials and with diseconomies of scope – that getting involve in too many different types of drugs are negatively affecting trial success rates. There is also some evidences that a drug is more likely to complete phase 3 if developed by firms whose experience is focused rather than broad (diseconomies of scope).

Lanjouw and Schankerman (2004) find that small owners have some disadvantages in protecting their intellectual property. Their results show that litigation risk is much higher for patents that are owned by individuals and firms with small patent portfolios. And from post-lawsuit outcomes, small patentees are at a significant disadvantage in protecting their patent rights because their greater litigation risk is not offset by more rapid resolution of their suits. This is likely one important reason why small owners may sell earlier in the drug development process – if you cannot protect it, better to sell before it is too late.

The effects of firm size have also been examined in financial industries. Chen, Hong, Huang, and Kubik (2004) consider the mutual fund industry, examining whether fund size erodes fund performance. Scellato (2007) studied Italian companies and found that only firms with lower financial constraints were able to maintain a sustained patenting profile by producing patents over time. The paper suggests the existence of an imperfect capital market in the Italian economy, particularly in the case of medium-sized companies, which tend to delay inefficiently the start of in-house R&D activities. This paper demonstrates that liquidity constraints inhibit the ability to obtain patents.

One of the pioneering works in utilizing USPTO patent data is Hall, Jaffe, and Trajtenberg (2001) that help provide available information to in-

vestigate on patent level information. They created a comprehensive data file on patents and citations, comprising all U.S. patents granted during the period 1963-1999 (three million patents) and all patent citations made during 1975-1999. Subsequently, Hall, Jaffe, and Trajtenberg (2005) provide patent citation related work. They explore the usefulness of patent citations, and examine its effect on boosting firm market value. Due to their contribution, NBER is now providing detailed and cleaned information on almost all aspects of patents from period 1963 to 1999, which most updated to 2002. Recently, a comprehensive version of USPTO patent information has been made available to public, and Figueroa and Serrano (2013) is the first study to explore patent assignment information using that database. They find that larger firms are more selective in patent acquisition than small firms. The conclusion is made based on differences in the patent suspension rate between large and small firms. If a firm buys a patent and does not pay continuation fees, then the patent will be suspended before its theoretical expiration date. Patent assignment data shows that patents bought by small firms have higher suspension rate than those bought by big firms. This observation reveals the possibility that in the buyer market for patents, there could be information asymmetry; namely, larger firms have greater expertise so that on average they buy better patents. I followed his use of patent assignment data and tested the performance differences between large and small firms' patent acquisition in this paper. But instead of using the patent suspension rate, I evaluate success in terms of actual sales revenue and drug market shares.

The adverse selection or lemons theory articulated by Pisano (2006) point out that small firms take advantage of asymmetric information to out-license their least promising compounds, retaining their more promising candidates to develop independently, which leaves a similar situation as auction: the winners' curse. Though this paper is not focusing on the adverse selection topic for buyers when deal with sellers with different sizes, the previous suggested test can be used to show if different sized buyers have similar information conditional on the same type of fair sellers – the asymmetric information issue not between seller and buyer, but within different buyers' group.

2 Data Sources

One of the most important data sources this paper relies on is the Orange Book from the Food and Drug Administration (FDA). The Drug, Price and Competition Act (Hatch-Waxman Act) requires the FDA to publish Approved Drug Products with Therapeutic Equivalence Evaluations, commonly known as the Orange Book. As a whole, they have 23,864 observations including both branded drugs and generic drugs approved by the FDA. In this paper, I focus on brand name drugs that are still on patent. The variables used to link different drugs and their patents are New Drug Application (NDA) numbers and Patent numbers. These two variables allow one to link the drug with its patent numbers, and thus enable us to link the Orange Book database with the database provided from USPTO. [9]

The Orange Book documents the applicant name of each drug when files are submitted. Importantly, the FDA allows firms other than the drug owner to apply for approval.[10] As a result, the applicant name can be different from the true drug owner and will not be valid information to document change of ownership. Thus, the applicant information from Orange Book will not be taken into account when constructing the patents transfer data. Another issue that must be mentioned is that the application number is not mapped uniquely to a drug name. Firms can submit multiple application files based on one chemical compound. This leads to many cases where one drug name is linked to multiple NDA numbers. This phenomenon occurs because individual drug applications usually fail. Firms can use one chemical compound for different indications (treatment targeting at high blood pressure as well as erectile dysfunction, for instance, Viagra) to increase the approval odds of that compound. For simplicity of data construction, I make a one-to-one matching for drug name and application number. If more than one application number is observed in the data for one drug, then only the most recent application number will be used.

The sales data of top-selling drugs are obtained from the drugs.com web-

[9] Orange Book Database has the applicant firm for the drug, which can be double checked from the NBER PATENT DATABASE or USPTO, to ensure the current ownership.

[10] For instance, Pfizer can allow GSK to assist with a drug development, and can assign GSK to apply for drug approval to the FDA using GSK as applicant name. Through the whole process Pfizer is the only drug patent owner, and GSK works as an assistance.

site. The data set reveals the top 200 (for years 2003-2010) selling drugs as well as top 100 ones (for years 2011-2013). Each drug trade name is linked to the seller and annual sales within United States.

The sales data of top-selling drugs are obtained from the drugs.com website. The data set reveals the top 200 (for years 2003-2010) selling drugs as well as top 100 ones (for years 2011-2013). Each drug trade name is linked to the seller and annual sales within United States. There are some weaknesses with the USPTO data that need to be noted. First, they are potentially incomplete. Some of the companies may not report all of their patent assignment changes. This is less problematic if such omissions are random rather than systematic. There is little reason to suspect systematic omissions, but it is at least a possibility that raises some concerns about bias. Another challenge is merging the USPTO data with the Orange Book. In order to identify an individual drug, a drug name needs to be linked to its patent numbers. Ideally, one drug uses only one patent. But it turns out many drugs have several patents on their molecule compounds, the production procedures, or how to deliver them properly. I assume that each patent is generating the same proportional revenue as the drug sales. For instance, if a drug is consist of 2 patents, then each patent will generate 50% of the revenue. Also, cases exist in which two different drugs share the same patent. In such cases, the patent would be considered to separately generating revenue from two drugs. And the total revenue the patent generates will be the cumulative sales from both drugs.

Detailed firm information is obtained from the COMPUSTAT Database. This database offers detailed US public firm financial information across documented years. This introduces variation for the same firm longitudinally. Thus, that the same firm could have different measures (for size, etc.) in different time periods. I included "R&D Expenditure", "Selling, General and Administrative Expense", "Total Revenue", "Total Asset". Since the database only includes information for public firms that have IPO in the US stock market, Germany or Japanese IPO firms are excluded, thus their information is missing.

Aside from our main data set, complementary data are also used. CPI data are extracted from Bureau of Labor Statistics, which are seasonal adjusted. Medical care is one of eight major groups in the Consumer Price Index (CPI). There are two medical care classifications, medical care commodities (MCC) and medical care services (MCS), each containing several item categories (strata). The category this paper uses is Medical Care Com-

modities, including medicinal drugs; and medical equipment and supplies. Center for Medicaid & Medicare Services (CMS) Household Survey data offers annual country-level prescription drug expenditures, which shows the total market size for all prescription drugs over time. Drug therapeutic classes are obtained from BlueCross and BlueShield, in total 13 different classes (for instance, anti-infective drugs, cancer drugs, cardiovascular drugs). Domestic firms may have an information advantage on who are potential patent sellers in U.S. compared to international firms. To control for this network effect, individual firm information is collected from web page to determine if they have headquarters in the U.S. Firms with headquarters are considered as domestic firms.

2.1 Data Description

Table 1 shows the patent transfer summary statistics as well as buyer firms' information. The targeted drugs are the top-selling drugs in the U.S. market from 2003 to 2013. The majority of these drugs have documented information from the FDA database, and approval dates range from 1991 to 2011. Further, the related patent transfers show records from 1985 till year 2012. In total there are 277 patent transfers documented [11]. The earliness of purchase variable measures how soon buyer firms purchase drug patents before drug approval. More specifically, this variable is measured as the difference between the purchase year and approval year. The variable "individual.seller" is a binary variable that indicates whether the patent seller is a group of individuals or a company. For group of individual sellers, the value is set to 1. This can be considered as the variation in sellers' characteristics, whether or not the seller is a powerful corporation or a group of start-up co-founders that lacks bargaining power. Within the observed transfers, on average half of them were sold by individual seller groups.

The patent buyers' names are documented for each transfer. In total there are 32 firms involved; the size distribution is strongly right skewed. Variables such as firm total assets, R&D expenditures, total capital holding, total revenue and marketing-related expenditures are annually data and are measured in millions of dollars.[12] Employee numbers are measured in thousands of personnel. Marketing-related expenditures include marketing costs,

[11] Since patents usually have expiration period of 20 years. I exclude transfer that's too early compared with drug approval date.

[12] The data have been discounted by CPI to constant dollars

Table 1: Summary Statistics

Statistic	N	Mean	St. Dev.	Min	Max
Purchase.Date	277	2,002.01	5.54	1,985	2,012
Approval.Date	277	2,002.42	4.34	1,991	2,011
TotalAsset	277	12,220.34	13,556.22	21.65	75,884.34
Employee.No	277	37.06	32.11	0.06	145.93
R&D	277	1,086.66	1,014.53	5.28	4,759.18
Capital	277	3,060.24	2,872.48	0.47	11,968.22
Revenue	277	8,518.44	7,963.20	1.27	31,109.45
XSGA	277	3,832.91	3,551.74	10.83	12,367.14
Marketing	277	2,726.92	2,625.59	2.85	9,393.66
Domestic.	277	0.65	0.48	0	1
Earliness(of.purchase)	277	−0.40	5.63	−15	13
Individual.Seller	277	0.52	0.50	0	1

operational costs, advertisement costs, and administrative expenditures [13]. The key variables of interest are R&D and marketing-related expenditures, since they are used to measure the firm's overall resources. To further distinguish firm characteristics, a domestic index is used to categorize if the firm is originated from the U.S. or not. 62% of the firms observed are domestic firms from the U.S.. The domestic information data are obtained from Wikipedia and websites containing company information.

Drug sales data are annual sales for the aforementioned top-selling drugs in the United States. They are measured in millions of constant dollars in 2003. Originally, there were 382 observed drug names for the years 2003 to 2013, but only 307 could be matched to FDA patent records.[14] Out of them, 145 drugs have patent transfer records. Drugs are categorized in 13 therapeutic classes, based on information from BlueCross and BlueShield (anti-infective drugs, cancer drugs, cardiovascular drugs etc.).

Figure 1 displays the cumulative sales for all 13 therapeutic classes from the years 2000 to 2012. The information is based on all the top selling drugs

[13]Marketing related expenditure is obtained by subtract R&D expenditure from Selling, General and Administrative Expense, value adjusted to be non-negative

[14]e.g. some of the top selling drugs in year 2012 and 2013 are generic ones, and when match drug names with patents, the generic drugs are excluded.

collected. Cancer drugs have an increasing trend overall, as well as central nervous system drugs (CNS) and hormones, and diabetes-related drugs. Drugs that belong to the blood modifying category rise and fall, where as anti-infective drugs sales remain steady over time.

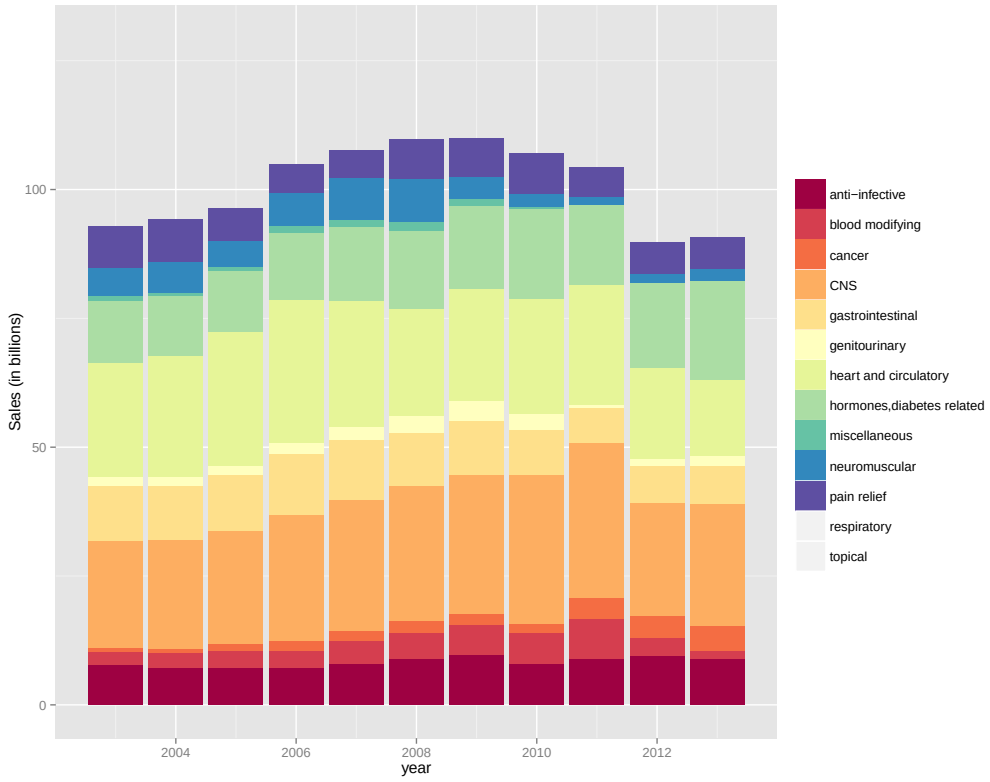

Figure 1: Annual Drug Sales by Therapeutic Classes

Table 2 shows the correlation matrix of the firms' size-related variables described in Table 1. All of the 6 variables are measurements of firm resource scale, and they are all strongly positively correlated.

2.2 Preliminary Illustrative Regression Results

Table 3 shows the effect of firm size on R&D and marketing expenditures. Here firm total revenue is used to measure firm size. Intuitively, firms with more revenue also have generally higher R&D, marketing expenditures and

Table 2: Correlation Matrix

	Total.asset	Employee	R&D	Capital	Revenue	Marketing
Total.asset	1	0.753	0.847	0.882	0.905	0.873
Employee		1	0.715	0.898	0.892	0.895
R&D			1	0.847	0.825	0.798
Capital				1	0.956	0.929
Revenue					1	0.976
Marketing						1

employee numbers. The "SGA.exp", which is the variable "sales, general and administrative expenditure" from the COMPUSTAT database, is interpreted as the aggregate expenditure of R&D plus marketing. The results show significant positive relationships between firm revenue with R&D and marketing.

But from the intensity point of view, Table 4 reveals that firms with higher revenues tend to have relatively smaller proportions of R&D and marketing expenditure. The intensity of R&D is the ratio of R&D expenditures to firm total assets. Similarly, intensity of marketing is defined as marketing-related expenditure divided by total assets, and SGA intensity is R&D plus marketing expenditure divided by total assets, etc.

3 Empirical Models of Patent Transfer effects

The empirical models examine patent transfer level behavior, and several different regression results are presented. Table 5 summarizes the names, descriptions and sources of the variables used in these analyses.

3.1 Effect of Firm Scale on Timing of Purchase

Equation 1 examines how a firm's size will affect drug patents purchasing time. The dependent variable is constructed as the difference between patent purchase time and drug approval time. This reveals how early the firm bought the drug patents prior to the approval date (timing), and is measured in numbers of years. Explanatory variables are measures of firm size, whether or not the purchasing firm is a domestic producer, therapeutic class of the drug patent and whether the seller is a corporate firm or group of individuals.

Table 3: Firm Size and R&D and Marketing Expenditures

	Dependent variable:			
	Employee.No	RDEXP	MRTEXP	SGA.EXP
	(1)	(2)	(3)	(4)
Revenue	0.001***	0.133***	0.272***	0.405***
	(0.00002)	(0.003)	(0.003)	(0.003)
Fixed.effect	Yes	Yes	Yes	Yes
Observations	957	993	845	845
R^2	0.681	0.722	0.930	0.945
Adjusted R^2	0.648	0.688	0.879	0.893
Note:				*p<0.1; **p<0.05; ***p<0.01

Table 4: Firm Size and R&D and Marketing Intensity

	Dependent variable: INTENSITY OF			
	Employee	RDEXP	MRTEXP	SGA.EXP
	(1)	(2)	(3)	(4)
Revenue	−0.00000***	−0.00000	−0.00000***	−0.00000***
	(0.000)	(0.00000)	(0.00000)	(0.00000)
Observations	957	993	845	845
R^2	0.356	0.001	0.169	0.145
Adjusted R^2	0.339	0.001	0.159	0.137
Note:				*p<0.1; **p<0.05; ***p<0.01

Table 5: Variable Description and Data Source

Var.name	Description	Data Source
Approval.year	year of drug's FDA approval	FDA
Purchase.year	year of patent transfer	USPTO
Individual.seller	whether seller party is group of individuals	USPTO
Earliness	purchase year minus approval year	FDA,USPTO
Total.asset	total asset from balance sheet	COMPUSTAT
Employee.No	number of employees	COMPUSTAT
RDEXP	expenditures on research and development	COMPUSTAT
XSGA	selling, general and administrative expenses	COMPUSTAT
Revenue	gross annual sales	COMPUSTAT
MRTEXP	XSGA - R&D expenses	COMPUSTAT
Capital	net operating assets (NOA)	COMPUSTAT
Domestic	whether the buyer firm originated from U.S.	WEB
Avg.sales	average annual drug sales	WEB
Total.sales	total drug sales across observed years	WEB
TC	Therapeutic classes of drugs	WEB

Alternative measurements will be used for firm size. Firm scale is measured by total assets, or company annual revenue. R&D intensities are measured in three different ways.

$$
\begin{aligned}
R\&D.intensity.1 &= \frac{RDEXP}{MRTEXP} \\
R\&D.intensity.2 &= \frac{RDEXP}{MRTEXP + MRTEXP} \\
R\&D.intensity.3 &= \frac{RDEXP}{Total.Revenue}
\end{aligned}
$$

$$
\begin{aligned}
Timing_{ijt} \quad &= \alpha_1 R\&D.Intensity_{jt} + \alpha_2 Firm.Scale_{jt} \\
&+ \alpha_3 Domestic_j + \alpha_4 TherapeuticClass_i \\
&+ \alpha_5 Individual.Seller_{ijt} + \xi_j + \epsilon_{ijt} \qquad (1)
\end{aligned}
$$

Table 6 refers to regression results of equation 1, and shows the effects of intensity measures as well as scale on the timing of patent purchases. The

use of alternative size measurements yield consistent results of the effects. Larger firm scale is significantly positively related to the timing of purchase, indicating that large firms purchase patents later (e.g., closer to approval date). This may be explained by the deep pockets of the big scaled firms, allowing them to afford to buy more costly later-stage products. On the other hand, all R&D intensity indexes have positive significant effects on the timing of purchase. This may be explained by the relative different objectives of the R&D and marketing departments. The R&D department is responsible for product development, so it seeks to keep high drug approval rate. Therefore R&D departments would prefer to buy later stage and thus safer drug products. On the contrary, the marketing department is rewarded for getting more drugs to advertise and sell, and has only benefit, not blame, on buying early products. The intensity ratio represents the influence of R&D department relative to the marketing department. Thus, firms with stronger R&D department would prefer to wait and buy patents at a later stage.

Whether or not the firm is domestically established does not have a significant effect on timing of purchase. But seller's type has an effect on the timing of transaction. Specifically, if the patent seller is a group of individuals, then the patent purchase would happen earlier than when the seller is a well-established company.

Table 7 shows the regression results using an alternative measure of the dependent variable "timing of purchase". It is the difference between drug FDA New Drug Application filing time and patent purchasing time. By definition, the filing time will be in prior to drugs' approval time. Our model specification follows that equation 1 as in Table 6, and the results are very consistent with Table 6. Firms' scale effects are positive and significantly related to purchasing time, just as in Table 6. The three R&D intensities show positive and significant effects on the dependent variable, demonstrating a similar pattern of postponement in patent purchases as Table 6: R&D intensive firms delay patent purchases. Overall, both Table 6 and 7 give essentially identical results.

Table 8 illustrates the effects of both firm scale and R&D intensity on the number of patents purchased by each firm annually. In total we have 123 firm-year observations, and across different measurements of firm scale and intensity, the results are consistent. A larger scale firm will purchase more patents each year on average, but more R&D-intensive firms will buy proportionately fewer patents than marketing-intensive firms. When a firm

Table 6: Effects of Scale and Composition on Timing of Purchase

	Dependent variable:			
	Timing of Purchase			
	(1)	(2)	(3)	(4)
RDintensity1	4.150***	3.271**		
	(1.326)	(1.313)		
RDintensity2			12.350**	
			(4.847)	
RDintensity3				1.249**
				(0.529)
log(Revenue)	5.147***	4.327***	4.026***	
	(0.592)	(0.618)	(0.580)	
log(TotalAsset)				6.557***
				(0.708)
Domestic.Firm	0.786	0.359	−0.177	10.312
	(12.617)	(12.289)	(12.314)	(11.240)
Individual.Seller		−2.897***	−2.852***	−2.151***
		(0.788)	(0.790)	(0.745)
Constant	−43.134***	−34.498***	−33.889***	−60.381***
	(10.121)	(10.134)	(10.106)	(10.500)
TC Dummy	Yes	Yes	Yes	Yes
FE	Yes	Yes	Yes	Yes
Observations	277	277	277	277
R^2	0.558	0.583	0.583	0.635
Adjusted R^2	0.472	0.499	0.500	0.562
Note:				*p<0.1; **p<0.05; ***p<0.01

Table 7: Alternative Measurement of Timing

	Dependent variable:			
	Alternative Measurement of Timing			
	(1)	(2)	(3)	(4)
R&D.intensity1	4.14***	3.63***		
	(1.03)	(1.03)		
R&D.intensity2			12.92***	
			(3.80)	
R&D.intensity3				1.21***
				(0.41)
Log(Revenue)	4.83***	4.35***	3.94***	
	(0.49)	(0.52)	(0.48)	
Log(TotalAsset)				6.65***
				(0.64)
Domestic	−14.65	−13.62	−6.19	13.53
	(21.76)	(21.42)	(21.40)	(19.81)
Individual.Seller		−1.71**	−1.68**	−0.94
		(0.67)	(0.67)	(0.63)
Constant	−31.69**	−27.20*	−31.06**	−65.28***
	(14.96)	(14.82)	(15.00)	(14.85)
TC Dummy	Yes	Yes	Yes	Yes
Fixed Effect	Yes	Yes	Yes	Yes
Observations	214	214	214	214
R^2	0.69	0.71	0.70	0.75
Adjusted R^2	0.62	0.63	0.63	0.69
Note:				*p<0.1; **p<0.05; ***p<0.01

is R&D-intensive, it can produce drug compounds in-house, therefore it does not necessarily need to buy as many from outsources.

Table 8: Effects of R&D Intensity on Number of Patents Purchased

	Dependent variable:			
	number of patents purchased			
	(1)	(2)	(3)	(4)
log(RDintensity1)	-1.319^{**}	-1.378^{**}	-1.604^{**}	
	(0.638)	(0.646)	(0.659)	
log(Revenue)	0.513^{**}			
	(0.248)			
log(RDintensity2)				-2.208^{**}
				(0.968)
log(TotalAsset)		0.506^{*}		0.515^{*}
		(0.266)		(0.266)
log(Capital)			0.738^{**}	
			(0.321)	
Observations	123	123	123	123
R^2	0.080	0.073	0.090	0.080
Adjusted R^2	0.057	0.052	0.064	0.057
Note:				*p<0.1; **p<0.05; ***p<0.01

3.2 Does Larger Scale Promote Higher Revenue?

3.2.1 All Drugs

I seek to understand if drug market performances (measured by average annual sales or cumulative sales) is affected by firm scale; specifically, marketing and R&D expenditures. Cumulative sales are the sum of overall drug revenue for all observed years. Average annual sales are cumulative drug sales divided by years in which the drug was sold. On average, it takes a drug at least 2 years to reach a normal level of sales from their first selling year. Further, the drug's last two years of sales are usually substantially below it's normal level of sales.

Equation 2 examines how firm scale differences will affect their drug sales performance. R&D expenditure, marketing related expenses and firm revenue are used as different firm size measurements. Sales are measured by two types of variable. The first is annual drug sales, and the second type is drug cumulative sales in all observed years.

$$\begin{aligned} Sales_{ijt} = \quad & \beta_1 SizeMeasure_{jt} + \beta_2 Domesticj \\ & + \beta_3 TherapeuticClass_{ijt} + \epsilon_{ijt} \end{aligned} \tag{2}$$

Regression results are shown in Table 9. Firm scale is measured by alternatively by total revenue, R&D expenditure, marketing expenditure, or R&D with marketing and therapeutic classes included in each regression model. Firms with larger scale do not show superior performance in drug sales when controlling for therapeutic classes.

Table 9: Simple Regressions

	Dependent variable:							
	avg_sale	total_sale	avg_sale	total_sale	avg_sale	total_sale	avg_sale	total_sale
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Marketing	0.010	0.025			0.005	0.181		
	(0.013)	(0.134)			(0.032)	(0.326)		
RD.exp			0.019	−0.013	0.011	−0.324		
			(0.025)	(0.254)	(0.061)	(0.616)		
Revenue							0.003	0.005
							(0.004)	(0.040)
Domestic	97.621	800.059	86.459	744.663	92.182	960.491	85.054	762.446
	(105.080)	(1,067.912)	(102.357)	(1,040.352)	(109.520)	(1,112.370)	(102.041)	(1,037.443)
TC Dummy	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	218	218	218	218	218	218	218	218
R^2	0.135	0.115	0.135	0.115	0.135	0.116	0.136	0.115
Adjusted R^2	0.075	0.054	0.076	0.054	0.071	0.051	0.076	0.054

Note: *p<0.1; **p<0.05; ***p<0.01

3.2.2 Drugs with Patent Transfer

The total number of drugs that has patent transfers, meaning, drugs acquired from outsource, falls to just 102. This is still largely due to our limited observation of firm scale measurements from the COMPUSTAT. To give a better visualization, I categorize firm size into 3 classes, big, medium or small. The graph is shown in Figure 2, using marketing expenditure as the scale measurements. The big firms are the top 10 out of all available firms by total assets; medium ones are from the top11 to top20; small firms are the remaining ones. As shown in Table 10, without taking into account the therapeutic classes or other controls, bigger firms tend to have higher sales on average but with greater variability. The results are consistent using alternative measurements of firm size, for instance, marketing expenditures, total revenue, total asset and Employee Numbers. This is also consistent with the results of DiMasi (2014).

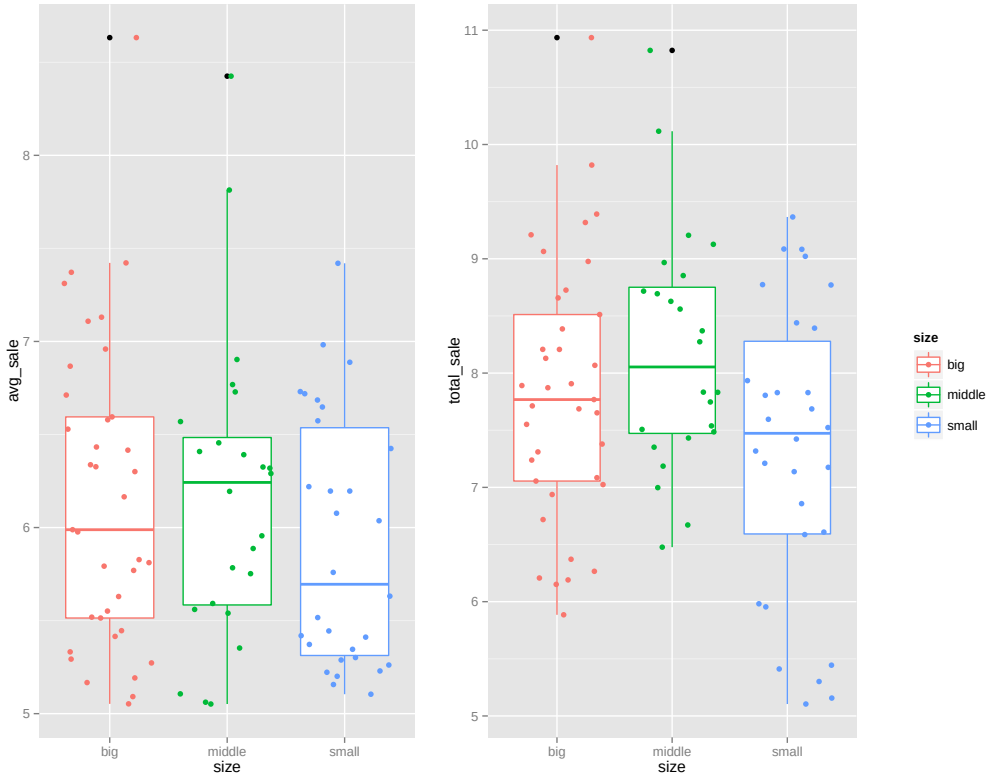

Figure 2: Drug Sales by Firm with Different Sizes

3.3 Determinants of Commercial Success

In this section, I include all possible factors that could contribute to the final drug payoffs, both by absolute sales and relative market shares. Specifically, I link each patent to it's trade name of the drug, so that I assume the ensuing revenue is due to that single patent. Using this approach, I can take into account the effect of each transfer on final commercialization. Since many drugs have multiple patents, this may be overestimating the effect of each patent transfer, however. As shown in equation 3, nonlinear effects of the two dimensions of firm overall resources (marketing and R&D expenditures) are taken into account. An additional dummy variable is created to indicate whether the transfer is an early purchase or not. The method is to compare the timing of purchase with all other purchases within a 6 year range [15]. If

[15]The range is set as 3 years ahead and 3 years afterwards

Table 10: Log Sales Distribution for Different Firms

	size	mean	median	std
log(avg.sale)	big	6.16	5.99	0.82
	middle	6.18	6.24	0.81
	small	5.92	5.70	0.68
log(total.sale)	big	7.82	7.77	1.14
	middle	8.18	8.05	1.05
	small	7.33	7.47	1.27

the purchase is made earlier than the median time, then consider it as an early purchase. We use this binary measure because the continuous variable "timing of purchase" is highly correlated with firm size (as in our first regression – see Table 6 above), to eliminate the multi-collinearity problem, I use the dummy to replace the continuous variable.

$$\begin{aligned} Payoff_{ijt} &= \beta_1 R\&D.Intensity_{ij} + \beta_2 Firm.Scale_{ij} \\ &+\beta_3 Domestic_j + \beta_4 TherapeuticClass_i \\ &+\beta_5 YearsOnMarket_{it} + \beta_6 Early_{ijt} + \xi_j + \epsilon_{ijt} \end{aligned} \tag{3}$$

Also, I include interaction terms of marketing costs and R&D expenditures with the Early dummy, to see how the two dimensions contribute to revenue depending on the timing of patent purchase. The effects of firm size on drug sales through early purchases are shown in Table 11. Both average annual sales and cumulative sales of drugs are used as measurements of drug revenue. To avoid overestimating the effects of each patent, and as a robustness check, the weighted average and cumulative sales are used as dependent variables. Sales are weighted by patent numbers. For instance, if a drug has 2 patents, and generate 100 million dollars of revenue cumulatively, then each patent will be weighted by half, and the revenue each patent generating is taken as 50 million dollars. Both linear and quadratic forms of different size measurements are included in the regression models. When included in quadratic form, marketing related expenditures contribute positively to drug revenue controlling for other drug and firm characteristics. Interestingly, both R&D and marketing expenses affect revenue through the interaction term with early purchase. More specifically, a stronger marketing division contribute negatively and stronger R&D division contribute positively if the drug is bought early. This could be due to the fact that R&D-intensive firms

are better able to identify better quality drugs in the early stages of development, even though their incentives are to delay purchases, as demonstrated earlier.

The index for domestic firms again does not have significant effect on sales. Log form of both sales and sizes are examined in Table 11. Fixed effects of the first year of sales are also included.

Table 11: Effects of R&D Intensity on Drug Sales

	Dependent variable:			
	log(sales)			
	(1)	(2)	(3)	(4)
log(RDintensity1)	0.645^{***}	0.606^{***}	0.389^{**}	
	(0.157)	(0.158)	(0.166)	
log(RDintensity2)				1.207^{***}
				(0.278)
log(TotalAsset)	0.561^{***}			0.518^{***}
	(0.074)			(0.077)
log(Revenue)		0.662^{***}		
		(0.085)		
log(Capital)			0.845^{***}	
			(0.099)	
Earliness	0.512^{***}	0.521^{***}	0.494^{***}	0.520^{***}
	(0.088)	(0.087)	(0.086)	(0.088)
Domestic	-0.008	-1.283^{**}	-3.504^{***}	0.340
	(0.461)	(0.552)	(0.723)	(0.500)
log(year_on_market)	0.715^{***}	0.744^{***}	0.743^{***}	0.723^{***}
	(0.065)	(0.065)	(0.064)	(0.065)
Constant	-0.494	-0.192	0.920^{*}	0.425
	(0.646)	(0.604)	(0.478)	(0.714)
Observations	456	456	456	456
R^2	0.602	0.604	0.614	0.604
Adjusted R^2	0.564	0.567	0.577	0.566
Note:				*p<0.1; **p<0.05; ***p<0.01

Table 12 follows the aforementioned regression equation 3, and presents the R&D intensity and firm scale effects on drug market shares as an alternative measurements of subsequent drug performance. The target drugs are categorized into sub-categorizes of therapeutic classes and market share of each drug within the sub-category is calculated as the dependent variable. [16] The regression results show that firms with larger scales have significantly positive effects on the drug market shares. Similarly, the R&D intensity plays a same role and contributes positively to the subsequent market shares. This can be explained as a selection advantage of the R&D intensified firms. The stronger their R&D department, the better they are in picking the more promising drug patents when acquiring from outsource. The overall results are very consistent with Table 11.

[16]For instance, if drug A and B belongs to category Anti-infection drugs, and annual sales as 100 millions, 100 millions respectively, then the market share for drug A will be 50 %, and same applies to drug B.

Table 12: R&D Intensity Effects on Drug Market Share

	Dependent variable:			
	market share			
	(1)	(2)	(3)	(4)
RDintensity1	0.15***	0.14***	0.13***	
	(0.04)	(0.04)	(0.04)	
RDintensity2				0.67***
				(0.16)
log(TotalAsset)	0.09***			0.07***
	(0.02)			(0.02)
log(Revenue)		0.12***		
		(0.03)		
log(Capital)			0.13***	
			(0.03)	
Earliness	−0.01	−0.01	−0.01	−0.01
	(0.03)	(0.03)	(0.03)	(0.03)
Domestic	−0.40***	−0.64***	−0.92***	−0.23
	(0.14)	(0.16)	(0.20)	(0.16)
year_on_market	0.02***	0.03***	0.03***	0.02***
	(0.003)	(0.003)	(0.003)	(0.003)
Constant	−0.81***	−0.81***	−0.56***	−0.98***
	(0.21)	(0.20)	(0.16)	(0.23)
Observations	456	456	456	456
R^2	0.55	0.55	0.55	0.55
Adjusted R^2	0.51	0.51	0.51	0.51
Note:				*p<0.1; **p<0.05; ***p<0.01

4 Theoretical Framework

Our behavioral economic framework discussed earlier assumes that R&D and marketing departments have different objectives that each deviate from pure profit maximization. These differences are able to persist due to information failures. That is, the CEO is unable to perfectly observe whether each department is behaving so as to maximize firm profits. As a result, the CEO relies upon markets that are readily observed but imperfectly correlated with profits (namely, drug approval rates for the R&D department and drug sales for the marketing department). An alternative framework can explain the empirical results we have observed in terms of a profit-maximizing model. And it is this framework to which we now turn.

One drug/patent is achieved after finishing n stages of phase tests. On average the firm Pharma can succeed to complete λ stages within one unit of time. The number of stages completed in one unit of time is distributed according to P(λ)

$$P(N = l) = \frac{e^{-\lambda}\lambda^l}{l!}$$

The value of completed patent (or drug) is V. The value of uncompleted patent is a function of square term of the number of finished stages, e.g. the value of a patent that has k stages left before drug approval is $\frac{n-k}{n}V$. Overall trial cost for each drug project $c(k)$ is a function of k.

The profit function

$$\Pi(k) = \sum_{l=k}^{\infty} \frac{e^{-\lambda} * \lambda^l}{l!} V - \frac{n-k}{n} V - c(k)$$

where the optimal time to buy patent is when there are k stages left to complete. λ takes value from 0 to 1.

$$\begin{aligned}\Delta &= \Pi(k) - \Pi(k+1) \\ &= \frac{e^{-\lambda}\lambda^k}{k!} * V - \frac{1}{n}V + c(k+1) - c(k)\end{aligned}$$

Firm should buy earlier (increase k) as long as Δ is less or equal to 0, and vice versa, the optimal $k^*(\lambda)$ solves

$$\Delta(k^*; \lambda) = 0$$

$$\begin{aligned}\frac{\partial \Delta}{\partial \lambda} &= \frac{e^{-\lambda}}{k!} k\lambda^{k-1} V - \frac{e^{-\lambda}\lambda^k}{k!} V \\ &= \frac{e^{-\lambda}\lambda^{k-1}}{k!}(k-\lambda)V\end{aligned}$$

If λ is less than k, then Δ is increasing in λ. Suppose k^*=k(λ) is the optimal k given λ, thus,
$\frac{\partial \Delta}{\partial \lambda} > 0$ whenever $\lambda < k^*$

For instance, consider two different firms, having different λ, which is respectively λ_1 and $\bar{\lambda}$, where $\lambda_1 \geq \bar{\lambda}$. (1)When $\lambda \leq$ k*, $\frac{\partial \Delta}{\partial \lambda} \geq 0$, for firm with a bigger λ (e.g. λ_1), :

$$\Pi(k^*(\bar{\lambda}); \lambda_1) - \Pi((k^*+1)(\bar{\lambda}); \lambda_1) \geq 0$$

The firm will be better off when delay the purchase (choose smaller k): the optimal $k^*(\lambda_1) < k^*(\bar{\lambda})$.

(2)When $\lambda >$ k*, $\frac{\partial \Delta}{\partial \lambda} < 0$, (in this case the only possible scenario is k=0):

$$\Pi(k^*(\bar{\lambda}); \lambda_1) - \Pi((k^*+1)(\bar{\lambda}); \lambda_1) < 0$$

The firm will be better off to not buy right at approval time.

5 Discussion and Conclusion

Building upon the prior work of Figueroa and Serrano (2013) and DiMasi (2014) on patent transfers and drug returns, this paper focuses specifically on drug patent transfer behavior in the pharmaceutical industries. By examining major top-selling drugs on the US market from 2003 to 2013, we explore the time preference of firms with different scale in purchasing drug

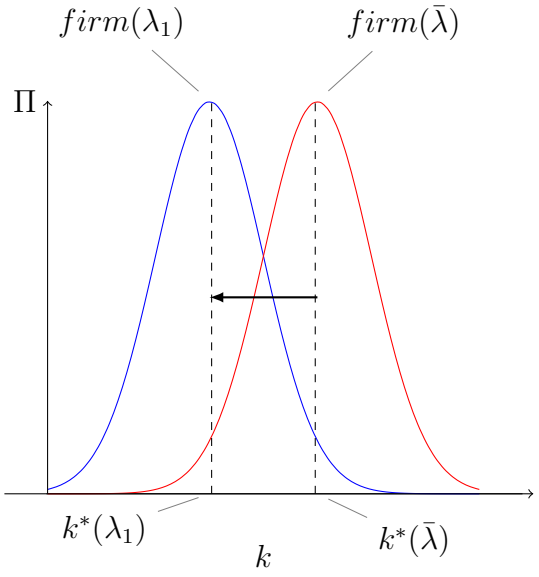

Figure 3: A Graphical Illustration

patents. Further, sales revenue of drugs is used to measure the economic returns of the purchased patents, so the commercial success of early purchases, and firm scale can be assessed. Here, firm scale is measured along two dimensions: R&D and marketing intensity. The reason for estimating these effects separately is that these two activities promote drug sales in fundamentally different ways. Marketing efforts can help increase publicity and popularity of drugs and thus contribute to higher revenue, conditioning on the quality of drugs. At the same time, marketing behavior might also affect perceptions of drug quality. R&D investment, on the other hand, help build stronger technical expertise divisions and may enable firms to identify and acquire better quality drugs. Therefore, when final sales are observed, it is potentially the result of both efforts , and major goal of this study was to quantify the contributions of each. If marketing decreases sales, they would stop marketing and vice versa.

When R&D and marketing expenses are separately considered, both significantly affect timing of purchase but in different directions. Firms with larger R&D divisions prefer to buy later than those with smaller R&D divisions. At the same time, more marketing-intensive firms purchase earlier than those with weaker marketing divisions. From the sellers' point of view,

non-corporate sellers sell earlier than well established company sellers. This is consistent with the fact that small start-up labs sell early due to liquidity constraints in completing experiments and tests. R&D intensity, which is the ratio of R&D expense over marketing expense (or revenue, etc.), is also used to check consistency. The results are similar as previous regression, showing that a higher R&D intensity suggests a postpone in patent purchasing. From both annual drug sales and cumulative drug sales point of view, firms in larger scales tend to have higher mean drug sales than firms in smaller scale. This result is based on top-selling drug observations over a decade, and is consistent with Dimasi's observation. This result is not surprising, because even if all firms are producing identical quality drugs, the network, marketing experience and advertising effort of bigger firms could boost their sales a lot compared with smaller ones.

Finally, in order to test the effects of both divisions on the selection of drug patents, I use interaction terms to illustrate the different roles the two divisions played in early patent purchases. A more R&D-intensive firm purchases early patents that are subsequently found to be more successful. So a stronger R&D division seems to help select the better drug patents out in early period, in which the uncertainty of drug patents is relatively high.

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