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Innovative Announcement Effects in the Pharmaceutical Industry via Stock Market Volatility

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I. Abstract

The pharmaceutical industry presents a unique opportunity to explore the intersection between product innovation and the corresponding market response. The emergence of life-enhancing drugs paired with the careful record keeping of the World Intellectual Patent Organization (WIPO) and the Federal Drug Administration (FDA) create a backdrop, which allows the relationship between announcements and firm value to be examined empirically. The motivational theory behind this paper stems from the efficient markets hypothesis (EMH), which suggests that public information such as patent application and publication would be incorporated efficiently in stock market returns. The relationship between R&D, stock market return, and patent generation is dynamic and an event study has widespread implications for investors and market strategists. This event-study design emulated from Fama and French's (1993) three-factor model allows for direct observation of the impact central nervous system (CNS) pharmaceutical innovation has on firm-specific returns. This paper finds a statistically significant increase in returns leading up to patent application for a CNS drug for domestically-traded firms, yet identifies a negative trend in returns surrounding the subsequent patent publication dates. Explained in more detail below, the decreasing returns firms experience as a firm's innovation nears completion can be explained by the models used which linearly capture this risk and generate decreasing returns.

II. Introduction

The pharmaceutical industry is driven by innovation. With the average cost to develop a new drug hovering around $800 million (Grabowski et. Al 2002), pharmaceutical research and development (R&D) holds 19% of all business spending on R&D (Ding 2014). This intersection between innovation and announcements provides an empirical opportunity to examine not only the impact of innovation on a firm's value, but on the validity of the efficient markets hypothesis. Given that the backbone of the pharmaceutical industry is intellectual property, this paper examines: how does CNS pharmaceutical innovation impact a firm's value? This paper studies the significance of announcement effects in stock price volatility when pharmaceutical companies request and publish patents on active ingredients in major antidepressant, antipsychotic, and anxiolytic drugs in light of EMH. Such an examination of announcement effects has never been done for patent application and publication dates, though Sharma and Lacey (2004) examined such effects surrounding FDA approval dates. I also extend my analysis to include FDA approval dates as a marker of external validity. This new question is interesting

and relevant both for investors, marketing strategists, and pharmaceutical researchers and developers. Because innovation signals progress regardless of outcome, investors could track and utilize patent announcements as an investing tool and a positive market signal that may be extended to other industries. On the firm side, marketers could time such events with strategic publicity to maximize firm profits and capitalize on firm value increases.

This paper defines an "announcement" as a firm-specific event or action that changes public knowledge of a firm by potentially increasing or decreasing a firm's value. Similarly, this paper defines an "innovation" as an entirely new CNS pharmaceutical drug. This paper examines the idea that the efficient markets hypothesis is false surrounding three types of announcements: patent application date, patent publication date, and FDA approval date of the innovations defined above. It seeks to disprove the idea that this information is already efficiently incorporated into security prices. Assuming an efficient market however, price on such event dates should only increase on the event date. However, assuming an inefficient market, security price should slowly increase beginning on event dates as information shifts from private to public knowledge.

Note that there are distinct times at which price changes may be expected. First is the discovery date, which corresponds to when a firm first applied for a patent via the World Intellectual Property Organization (WIPO), which this paper calls the application date. Second is the patent publication date, when the patent office releases information about the application. Third is the date of the Federal Drug Administration (FDA) approval. These distinct times are classified as announcements by this paper.

According to the United States Patent and Trademark Office, a member of the public cannot obtain "direct physical access" to *pending* applications, but can obtain them online, by mail, etc. (USPTO.gov). Because this is difficult for the uninformed member of the public, and

given that firms do not "announce" pending applications as they may negatively affect a firm's value if left unpublished, I expect that patent applications as announcements will have no effect on a firm's security price, thereby leaving no room for investor profit. Stock price will already have incorporated this information by insiders at the time of the event. However, I expect there to be a significant price change around patent publication and FDA approval dates. Literature surrounding FDA approvals can be inconsistent, but that of drug development via patents might provide more reassuring and significant social effects, which is the central focus of this paper.

This paper proceeds by examining the wide variety of literature in this field beginning with an overview of EMH and its validity as an event-analysis tool, extending EMH to the pharmaceutical industry by delving into drug development as an announcement and potential signal to investors, and finally on patenting an the financial implications of innovation. Following the literature review, the paper is organized as follows: an overview of data sources and compilation techniques, regression and analysis methodology, results, and finally a conclusion.

III. Literature Review

i) EMH and Reaction to News

A market in which prices at all times completely reflect all available information is efficient (Fama 1970). The strong form of EMH suggests that all information, public or private is reflected in market prices, while the semi-strong form states that only public information is incorporated into prices. The weak form of the EMH suggests that only previous market information such as interest rate is reflected in security price. Stated more directly in Section VI, this paper tests the strong form of the EMH, which would result in no net price change surrounding events. In their technical analysis, Rehman and Khidmat (2013) justify EMH by stating that all public information (characteristic of the weak EMH form) is reflected in the listed

stock price. The stock market overreaction hypothesis, however, challenges EMH, stating that unanticipated news or innovations leads to potentially benefiting, exaggerated trends that eventually correct themselves (Gregoriou 2010). Due to the wide variety of complex, sector-based information surrounding the factors comprising a stock price, prediction of stock volatility is difficult. Rehman and Khidmat (2013) examine the multitude of financial indicators that determine security price, while Eizaguirre et al. (2009) find that changes in volatility are directionally heterogeneous based on sector and location.

There is no question that new products and announcements have widespread economic effects. However, the magnitude and direction of announcement effects have been studied to various degrees, generally finding consistent and intuitive results. Beaver (1968) first uncovered that positive earnings announcements increase share prices, a finding that has been confirmed and studied further. Savor and Wilson (2013) similarly find that the average announcement-day excess returns from 1958 to 2009 was 11.4 basis points compared to 1.1 basis points for other days. Chaney *et al.* (1991) also found a small increase in stock price during the three days surrounding the announcement, and Flannery and Protopapadakis (2002) similarly find an announcement effect on returns from announcement news sensitivity by looking at volatility of various shocks.

While Flannery and Protopapadakis (2002) focus on announcement news, Savor and Wilson (2013) look at expected returns, a more relevant subject for investors requiring compensation for their risk-bearing behavior. They find positive expected returns of announcement effects stemming from news about inflation, unemployment, or interest rates, while most other literature focuses on innovative news or technological advancements. Sharma and Lacey (2004) find a significant effect in stock volatility in a three-day window surrounding innovative announcements, though no effect was found outside the event window. This result

empirically demonstrates that unanticipated positive news is *eventually* incorporated efficiently into stock prices, a result consistent with weak EMH, given a subsequent time lag.

Other announcement analyses, such as Rodriguez and Valcarcel (2012), find that the impact of negative news items on stock prices is larger than positive news items. Positive product announcements are indicative of true firm innovations, which face little to no competition and allow firms to obtain high profits when that information becomes public. While a positive profit margin is likely to disappear, it still provides an incentive for firms to create sustainable growth through continued product innovation.

Studies that analyze the effect of innovation in light of the EMH give mixed results. Eddy and Saunders (1980), find no effect of new product announcements on monthly stock returns, while Wooldridge and Snow (1990) find a positive reaction to product news that quickly declines after a ten-day window. These varied results suggest that information is either absorbed more quickly than imagined, favoring the strong form of the EMH, or that markets ignore some information. Regardless, the effects are difficult to isolate across industries. In the interest of maintaining consistency with previous literature, this paper also has an intra-industry focus in the pharmaceutical industry.

ii) The Pharmaceutical Industry Intro: Development and R&D Intensity

Competition and innovation in the pharmaceutical industry hinges on technological progress, and progress in the form of innovative drugs can increase life expectancy and quality of life. The pressure to innovate is paired with a complex development process that usually takes about fifteen years—from drug discovery to FDA approval—making development trends somewhat difficult to track (Ding 2014). There is vast literature that studies innovation, some of which concentrate on Central Nervous System (CNS) drugs due to their arguable classification as luxury goods from a public health perspective. CNS drugs are likely to cause a market effect

because innovation and technological advancement are strong indicators for beneficial investments and sustained growth (Duggan and Goyal 2012). CNS drugs act on the brain and spinal cord and include the therapeutic drug classes that make up the dataset for this study: antidepressants, antipsychotics, and anxiolytics. Drugs in this category have high technological advancement and comparative effectiveness, as defined by Morgan et. al (2008), which makes them key components of the innovation effects on the market and an interesting indicator for innovative analysis.

The drug development process is extremely complex and highly regulated. As mandated by the FDA, clinical trials occur in multiple stages as long as 14 years after the synthesis of a new compound (DiMasi 2001). Only two statistically significant positive trials are needed to obtain drug approval and many companies hide countless negative trials leading to more expensive drug development and a positive publishing bias (Kirsch 2010).

Due to the high level of technological advancement, development of drugs such as antipsychotics or antidepressants require large investments in R&D. Grabowski et al. (2002) estimates that the average cost of developing a new drug is about $800 million. Civan and Maloney (2006) show that global pharmaceutical companies adjust their R&D priorities according to prevalent diseases in the United States, and Whittaker's survey (2005) pinpoints an astonishing increase in severe mental illness in the United States over the past fifty years. Pharmaceutical R&D holds 19% of all business spending on R&D (Ding 2014), yet research and development of innovative pharmaceuticals is risky and uncertain, so high R&D costs must be offset by revenue potential (Heible 2013). Rosiello and Orsengio (2008) find that the clustering of biotech companies is driven by resource funding allocations and can lead to vertical integration, where a majority of innovation comes from only within-cluster and could prevent market entry.

Because of the strong focus on innovation and the high allocation of funds to R&D, the pharmaceutical industry is ideal for empirical research on stock price overreaction as new products signal increasing internal capabilities to innovate according to Geroski et. al (1993). Sharma and Lacey (2004) empirically examine whether product development pays and find results consistent with the efficient market hypothesis: that the market responds to FDA approval of a drug positively. They analyzed the effects of new products on firm value by using an event study methodology described in Section VI. Rodriguez and Valcarcel (2012) results contrast this by using an ARMA-GARCH dynamic economic model to detect large price changes in stock prices in the seventeen largest pharmaceutical firms and find that only 10 of 1721 FDA approvals of new drugs were related to abnormally large returns. The difference in results stems from Rodriguez and Valcarcel's (2012) finding that the market responded more severely to negative news items; unlike Sharma and Lacey (2004), they focused not on FDA approval dates, but on the R&D process, where there is a high probability that a drug will be rejected in clinical trials.

iii) Pharmaceutical Patenting and Financial Implications of Innovation

Because patenting is the backbone of innovative intellectual property, patent protection can serve as a firm performance indicator. It is worth noting that a World Bank survey showed that intellectual property protection was a central factor in global investment decisions in pharmaceuticals (Santoro and Gorrie 2005). Pakes (1985) claims that the number of successful patent applications is a measure of the firm's investment in incentive activity (new product development projects) and can act as an indicator of output through the stock market's firm valuation. The patent is a more direct valuation of successful research than other performance indicators. Duggan and Goyal (2012) find that there are heterogeneous effects on retail drug prices by type of pharmaceutical product patent, specifically those claiming the active ingredient.

Golec *et al*. (2010) extends one innovation concern by linking stock prices to future R&D spending, and finds that price regulation such as the Health Security Act had a negative effect on stock prices and firm R&D spending. Lee and Chen (2009) also find a negative effect on shareholder value related to firm size, demonstrating that amount allocated to investment is impactful in investor signaling. Delving deeper into the effect on research and development effects, Berk, Green, and Naik (2004) examine the return dynamics of new technologies and find that there is extensive uncertainty embedded in research and development projects; this risk potentially diminishes potential profitability after technical progress. Sharma and Lacey (2004) suggest that it may be beneficial for firms to refrain from hyping new products due to the large effect of negative information on the financial markets. However, by focusing on positive product innovation, this paper aims to avoid the asymmetrical response to new product development. One potential bias worth noting is that positive product innovation analysis might not necessarily capture the complete valuation of a pharmaceutical firm.

While various techniques have been used as analysis tools in innovation event studies, this paper emulates the Fama-French (1993) model as an expansion of the Capital Asset Pricing Model to explain the announcement effects in pharmaceutical innovation. Brown and Warner (1985) conclude that the characteristics of daily stock return data presents few difficulties for event studies and find that simple methodology based on the market model is well specified and powerful under many conditions. Given this, CAPM provides a baseline to examine the effect of the patent and FDA announcements.

iv). CAPM Methodology and Background

The Capital Asset Pricing Model (CAPM) was used first to estimate market parameters alpha and beta and is widely considered to account for 70% of stock price volatility (Corrado

2010). Developed in the early 1960s by William Sharpe (1964), Jack Treynor (1962), John Lintner (1965) and Jan Mossin (1966), for any firm-specific security *i* at time *t*, the model is as follows: $(R_{it} - R_t) = \alpha + \beta(R_{mt} - R_f) + \varepsilon_{it,}$ CAPM allows expected rate of return to be calculated for an asset and was used in this paper as a baseline to maintain consistency with existing financial literature. Here, $(R_{mt} - R_f)$ is a market portfolio that takes the value weight of all firms incorporated in the US and listed on the NYSE, AMEX or NASDAQ that have a CRSP (Center for Research on Security Prices) share code of 10 or 11 at the beginning of month *t.* $R_{f,}$, the one month treasury bill rate, or the risk-free rate, is subtracted from R_m. ε_{it} is the error term, and β is systematic risk. CAPM suggests that an investor's equity cost is determined by beta.

v) The Fama-French Model

The Fama-French (1993) three-factor model, an expansion of CAPM, which primarily estimated beta, was used to determine what was driving the returns. The Fama-French model estimates market parameters which include R_m-R_f, SMB (the small market capitalization minus big), and HML (high book to market ratio minus low). SMB is a covariate that takes into account size, or the extra risk associated with small company (cap) stocks. Small-cap stocks tend to generate higher returns than large-cap stocks in the long run, though this comes with higher risk. HML is a covariate that accounts for the value of owning stocks that have been undervalued and tend to generate higher returns than growth stocks in the long run. This model expands on the capital asset pricing model by adding the two factors, SMB and HML, and explains 90%-95% of the variability in returns (Corrado 2010). Data were gathered from Kenneth French's online database and use six value portfolios formed on size and book to market by the Center for Research on Security Price. This dataset incorporates all firms listed on NYSE, AMEX, and NASDAQ from July 1, 1926 to December 31, 2014. The model is estimated as follows:

$$R_{it} - R_f = \alpha + \beta_{1(}R_{mt} - R_f) + \beta_2 SMB + \beta_3 HML + \beta_4 1(dayafter) + \varepsilon_{it}$$

The model includes a dummy variable called 'dayafter' which estimates the difference in returns one day after the event date. Regressional outputs depicted in the appendices display the variety of event window indicator variables used. Molecule fixed effects were included to allow for within-molecule variation observation. SMB was calculated as the average return on three small portfolios minus the average return on three large portfolios. HML was calculated as the average return on the two value portfolios minus the average of the two growth portfolios.

SMB =[⅓ (small value + small neutral + small growth) - ⅓(large value + large neutral + large growth)]

HML = [½ (small value + big value) - ½(small growth + big growth)]

The inclusion of these variables by Fama and French (1992,93) separates stock returns into three distinct risk factors: beta (the brainchild of CAPM), size (which takes into account the extra risk in small stocks and the potentially higher returns), as well as value (which takes into account companies that have lower market values compared to intrinsic value). Berk, Naik, and Green (1999) validate this book-to market approach used by Fama and French, and explicitly state in their model development of expected security returns that this variable (used in the generation of SMB and HML) appears to justify the fluctuation in a firm's risk.

In his 2002 critique, Griffin finds that the Fama-French three factors are country-specific and concluded that the model performs best when localized within-country. Due to this, this paper focuses primarily on domestically traded public firms, though an international extension can be found in *Appendix 3*.

The vast and varied literature linking R&D to firm security price only highlights the importance of understanding the market structure of this industry through announcement effects. I expand on the above literature by using the Fama-French model to examine the effect of announcements on firms in one extremely dynamic industry. Examining announcement effects in pharmaceuticals will increase understanding of the mechanisms in which innovation contributes to both economic growth and firm value.

IV. Data Sources and Compilation Techniques [1]

Data were compiled as three different panel datasets surrounding the three different announcement dates: patent application, patent publication, and FDA approval date. Each panel dataset included all innovative antidepressant, antipsychotic and anxiolytic drugs beginning in 1974 and spanning twelve different domestic pharmaceutical companies traded on either NYSE or NASDAQ. The multi-dimensional panel data contains molecule, company, and exchange differences occurring through time. Within-molecule and variation is the primary interest of this paper as molecules are perfectly collinear with a pharmaceutical firm due to the nature of a patent giving exclusive rights to one firm. However, biotech clustering and the intensive cost of R&D forces mostly large companies to innovate and innovate frequently, making the molecule, and not firm the relevant observation.

Like Duggan and Goyal (2012), CNS molecules were the pharmaceuticals of interest and were compiled into a list of three therapeutic drug classes—antidepressants, antipsychotics, and anxiolytic molecules from the FDA Orangebook[2] and the RxList[3]. To ensure econometric accuracy, assume there is no selection bias; molecules were selected as a complete list of

[1] In order to ensure accuracy and robustness of the date, I sought help from professional librarian Jennie Gerke at the University of Colorado at Boulder. She is the Head of the William M. White Buiness Library.
[2] http://www.accessdata.fda.gov/scripts/cder/ob/
[3] http://www.rxlist.com/script/main/hp.asp

innovative CNS molecules to ensure accuracy of the sample. Molecules that were excluded were randomly dropped as a result of insufficient or lack data. Proper randomization was achieved by allowing each molecule to have the potential to be included in the compiled panel datasets. Molecules that have been taken off the market were dropped. Non-innovative molecules, or molecules that lack a new neurological mechanism or were chemical, generic variants, were not included in the dataset. Patent application date, publication date, and innovator company were obtained from the World Intellectual Patent Organization (WIPO)[4] for each innovative molecule and this data was crosschecked against information from Google Patent[5]. Daily stock price closing data were gathered and matched to molecule and innovator company through Yahoo!Finance[6] historical pricing. If stock data were not available on Yahoo!Finance, then data were obtained from the ThomsonOne online database. Molecules patented by private companies with no historical stock price data were dropped. If historical stock price data for a firm were not available for the corresponding patenting dates, those observations were dropped. Molecules patented by companies that later were acquired by larger firms were also dropped because the larger firms historical stock prices would not have reflected the smaller firm's value accurately during the time of the announcement. Shown below is a descriptive table of the data separated first by announcement date and then by both drug class and firm type.

[4] http://www.wipo.int/portal/en/index.html
[5] https://www.google.com/?tbm=pts&gws_rd=ssl
[6] http://finance.yahoo.com

Table 1: Summary Statistics

Events				Total
Application Date	**CNS Drug Class**	Antidepressants	27	44 Molecules
		Antidepressants	12	
		Anxiolytics	5	
	Pharma Firms	Domestic	12	21 Firms
		International	9	
Publication Date	**CNS Drug Class**	Antidepressants	28	46 Molecules
		Antipsychotics	13	
		Anxiolytics	5	
	Pharma Firms	Domestic	12	21 Firms
		International	9	
FDA Approval Date	**CNS Drug Class**	Antidepressants	5	10 Molecules
		Antipsychotics	4	
		Anxiolytics	1	
	Pharma Firms	Domestic	7	7 Firms

If a molecule was patented by an international company and not traded domestically on NYSE or NASDAQ, stock prices were converted to U.S. dollars using matched historical exchange rate data changing through time and added as a second tier of analysis for robustness. This second tier of analysis added ten innovative molecules from nine different international firms on five different exchanges shown below. As stated above, the inclusion of international firms, as found by Griffin (2002) may have biased the regressional analysis and was therefore solely included in *Appendix 3* as an extension for completeness and robustness. *Table 2*, below, shows international firms with innovative molecules that were included in the analysis of *Appendix 3*.

Table 2: Internationally-traded firms with innovative molecules

Firm	PARS	FQX	NEUR	AKZOY	HLUYY	HES	XANO	CORX	RHHVF
Exchange	OTCMKTS	DU	CPH	OTCMKTS	OTCMKTS	AMS	B.ST	OTCMKTS	OTCMKTS
Currency	USD	EUR	DKK	USD	USD	EUR	SEK	USD	USD
Molecule	1	1	1	2	1	1	1	1	1

To maintain consistency with existing financial literature, the Fama-French daily factors were gathered for inclusion in the Fama-French three factor model: SMB, HML, and Rm-Rf. These were obtained from Kenneth R. French's Online Data Library[7] and are calculated as outlined above in the review of literature.

A variable called 'time index' allowed for stock return data to be compiled as a panel and ranges from -250 to +14, equaling zero on the announcement date. Indicator variables were generated to observe an effect on returns for specified periods. For example, the indicator variable 'twoweeksbefore' takes the value one for return data in the pre-event window, when 'timeindex' = -14 to 0. Indicator variable 'dayafter' takes the value one only when 'timeindex'= +1.

Generally, patent event windows surrounding the outlined announcement dates did not overlap, which allowed estimations for parameters of the normal return model to not be influenced by other patent announcements. However, due to the nature of the panel data compiled and used in this paper, a dummy variable was introduced in order to eliminate innovative molecules introduced by the same company in the overlapping event window in the patent application announcement dataset. Due to this restriction and in order to reduce this noise, five innovative molecules in the application date panel have smaller historical windows and two innovative molecules were entirely dropped as their event dates perfectly overlapped.

[7] http://mba.tuck.dartmouth.edu/pages/faculty/ken.french/index.html

To observe further differences across time, a variable called 'quarterly time trend' was introduced and takes the value one through four depending on the business quarter in which the patent announcement or FDA approval occurred. This variable was thought to observe seasonal differences in pharmaceutical innovation trends.

V. Pitfalls and Biases of Data Collection

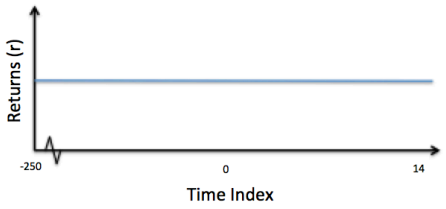
One pitfall of solely focusing on pharmaceutical innovation is that innovator companies potentially sell published patents, so there is a lack of consistency in data matching with FDA approval date. This led to a much smaller panel dataset surrounding FDA approval date and therefore less econometric power. Secondly, many drugs in this class are widely used in Europe and Asia, but not approved by the FDA in the US, yielding an even smaller FDA approval dataset.

It is also important to note the high failure rate of pharmaceuticals during the clinical trial period (Fernandez and Huie 2007). Despite this, the effect of patent application may signal to investors that a pharmaceutical firm is entrepreneurial, innovative, and worth investing in due to the strong research and development initiatives. The theory behind this paper suggests that an innovation signals to investors that a firm is growing. Because innovation is necessary for sustained growth and is a trial and error process by nature, successful or even unsuccessful innovations should positively increase a firms value as seen in an increase in stock price. Unsuccessful new ventures still display an entrepreneurial, profit-oriented firm that investors are likely to demand.

VI. Methods

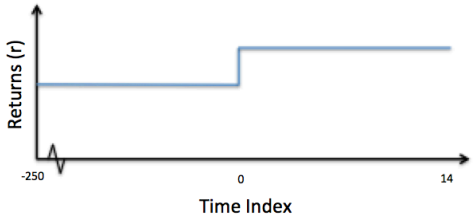
The following hypothesis is examined both assuming efficiency and inefficiency. The corresponding diagrams outline the expected price change.

H_0



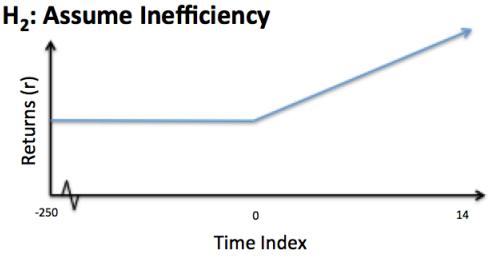
H_0: There will be no net price change surrounding the announcement of a patent, as "new" information is already efficiently incorporated into security prices in the strong model via insider trading or other information leakage.

H_1: Assume Efficiency



H_1(Assuming efficiency): Because the market is efficient, prices quickly spike surrounding announcements before obtaining a new equilibrium price. Therefore, there is only room for investor profit contingent on patent publication or other information right on the announcement date. In this weak form of the efficient markets hypothesis, security value will change when privately held information becomes public.

H_2: Assume Inefficiency



H_2 (Assuming inefficiency): Because the market is inefficient, prices will slowly increase following the event date as the information becomes publicly known, leaving room for investor profit.

Shown below, *Figure 1* depicts the three-day annualized average returns (R_{it}) of domestically-traded firms surrounding application date, while *Figure 2* similarly depicts R_{it} surrounding patent publication date. A general trend of increasing returns following the event date is observed.

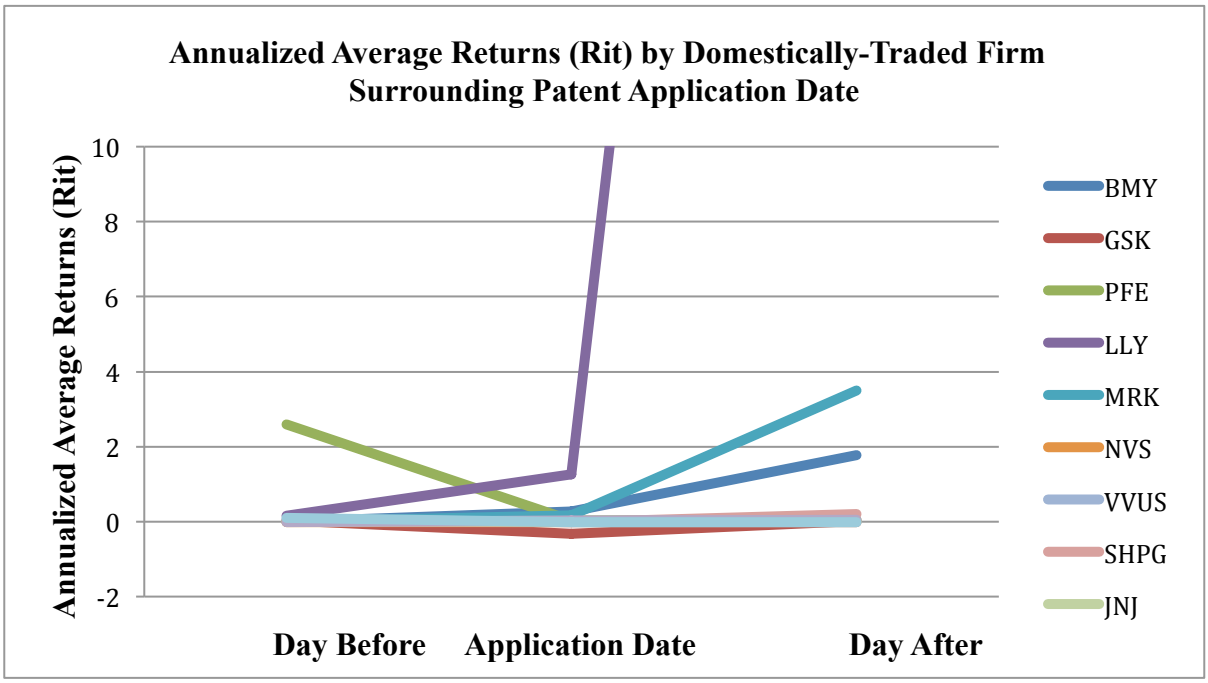


Figure 1

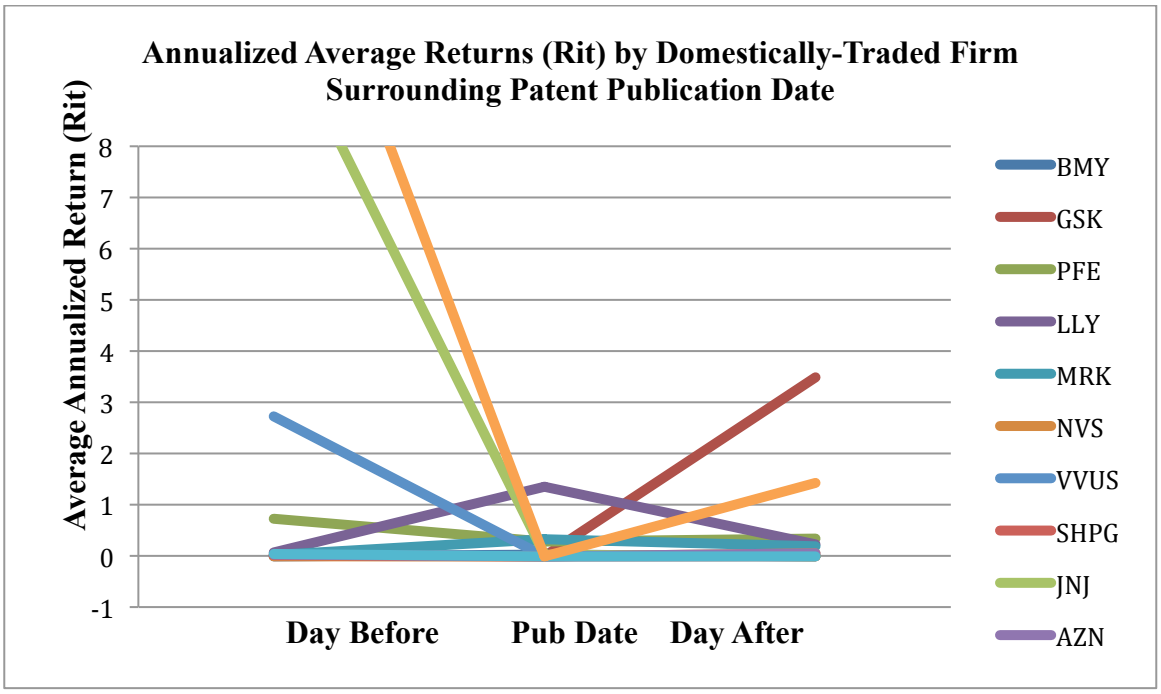


Figure 2

i). Event Study Methodology

My event study methodology is emulated from Sharma and Lacey's (2004) event study on product development outcomes and firm valuation. A 236 day period was used to estimate market parameters (-250 to -14) and a 29 day event period included the event window (day -1, 0, and +1), a pre-announcement window comprised of two weeks of daily returns (-14 to -2) to check for information leaks, and a post-announcement window (+2 to +14) to demonstrate persistence. This event study methodology allows annualized daily returns for security *i* to be linearly estimated to returns on the market portfolio and maintains consistency with financial literature that examines announcement effects.

Daily historical stock price data was gathered from Yahoo!Finance historical pricing and ThomsonOne, and returns were calculated as follows where P_{it} is the percentage change in stock price (P) for firm *i* at time *t*.

$$R_{it} = (R_{t-1} - R_t)/R_{t,}$$

The following depicts the calculation performed to annualize R_{it} where 250 is the average number of stock trading days per year (Sharma and Lacey 2004) and Rf is the risk-free daily treasury bill rate acquired from the Federal Reserve.

$$R_{it}\text{-}R_f\text{: } (1+P_{it})^{250}\text{-}1 - R_f$$

The multi-layered tiered regressional analysis this paper uses can be observed in *Figure 3*, which outlines the various regressions performed for the three specific event dates using both the CAPM and the Fama-French Model and various indicator variables included.

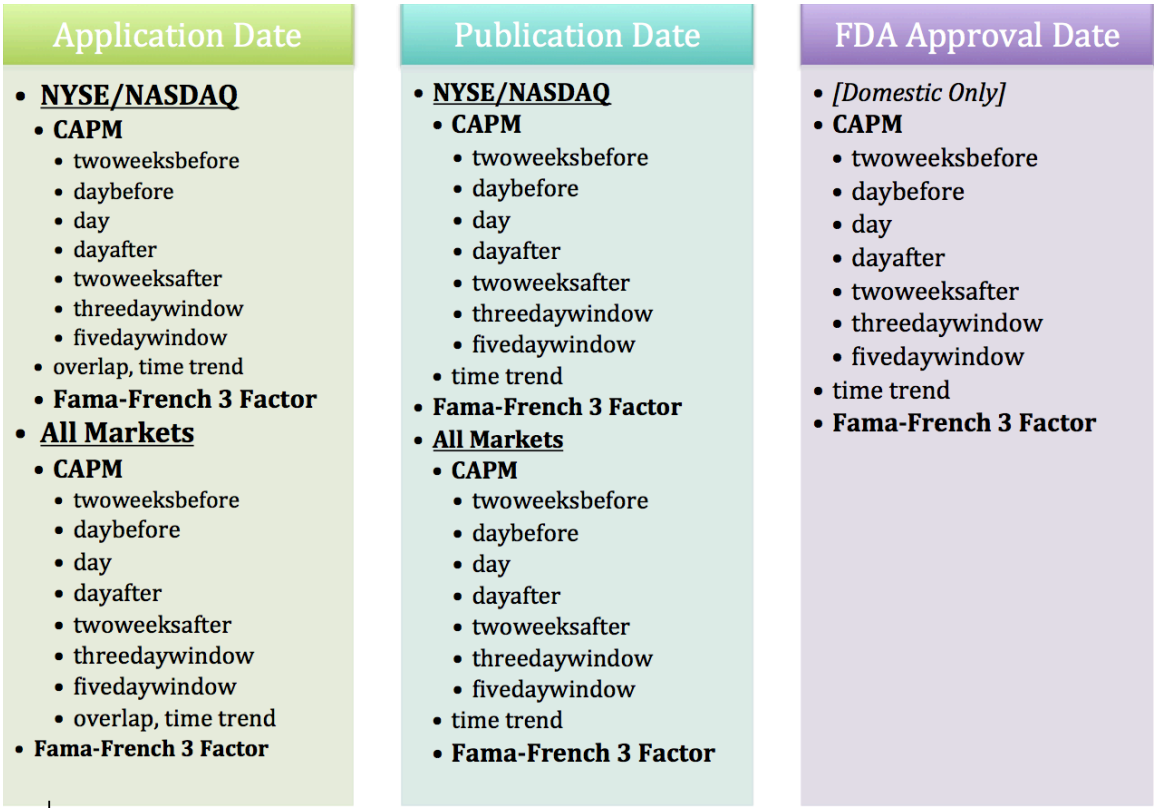


Figure 3: Tiered Regressional Analysis

ii). Specification of empirical design to estimate the Capital Assets Pricing Model (CAPM) and the Fama-French Model extension is as follows:

To examine the impact of announcements on the value of a firm's equity, it is necessary to posit a relationship between information and a price increase. (MacKinlay 1997).
This paper maintains general conditions under which ordinary least squares (OLS) accurately estimates both CAPM and the Fama-French Model. Under the following assumptions, OLS can be considered efficient. Both models assume that asset returns are jointly and multi-variately normal and are independently distributed through time. By assuming a normal distribution, both models can be correctly specified.

The gain from extending analysis to the Fama and French's three-factor model allow for the restrictions and biases of the CAPM to be eliminated and increase the explanatory power of the model. Though CAPM is linearly estimated and follows the assumed joint normality of returns, biases of CAPM include the disequilibrium of present value and it's central focus on risk. These biases ignore other factors that contribute to the variation in returns such as size and value. Fama and French (1996) postulate that beta alone cannot explain expected returns.

CAPM removes the portion of the return related to variation in the market return that reduces the variance of the abnormal return. Fama and French use a different asset pricing theory that combines other risk factors in a linear fashion. Fama and French (1992) state that performance of portfolios can be evaluated by comparing returns with returns of benchmark portfolios with similar book-to-market equity characteristics. Malin (2004) states that the CAPM alone is not sufficient to describe the variation in equity returns and argues that the performance should be evaluated using the multifactor model.

VII. Results and Discussion

i) Effect on Patent Application Announcement Date

Appendix 1 illustrates regressional outputs for seven indicator variables surrounding patent application and publication date for domestic firms in the CAPM model. Two weeks before and the day before show statistically significant increases in returns surrounding application date (in Table 1.1): 78.94% and 269.88% annualized increases respectively. Similarly, we observe a 142.46% increase in during five day window. Extending the analysis to include covariates SMB and HML increases the model's R-squared value and therefore the model's fit. In *Table 2.1*, we see 78.5% increase in annualized returns in the two weeks before patent application date and a 268.45% increase in returns on the day before application date. This effect in the Fama and French's model of domestically-traded firms surrounding patent application date allows us to reject the null hypothesis (which states that the market is efficient and already incorporates public and private information, thereby displaying no increase in returns) in favor of alternative hypothesis two which demonstrates a slower, inefficient price increase leading to this patent announcement date. The significance of the five-day window demonstrates this persistent returns increase even slightly after the event date.

ii) Effect on Patent Publication Announcement Date

Table 1.2 portrays negative statistically significant returns during the two weeks before patent publication date and on the patent publication date using the CAPM. We see a statistically significant decrease of 197.46% in the two weeks leading up to patent publication and an even more dramatic decrease of 671.87% on the event date. *Table 2.2* similarly includes Fama and French's factors SMB and HML to observe effects surrounding publication dates, yet depicts statistically significant decreasing effect on returns is still observed both two weeks before and

on the patent publication date. This effect can be explained by a phenomenon discovered by Berk, Naik, and Green in their 2004 analysis, mentioned in the above review of literature.

Berk, Naik, and Green (2004) identify a CAPM relationship that explains the decreasing risk of a new venture over time. In the case of patent publication date, the large negative returns signal the decreasing risk, therefore decreasing returns of the CNS pharmaceutical innovation. Systematic risk is highest early in the stages of new ventures, which may explain the positive, significant coefficients during patent application date, where there is a much higher failure rate. Berk, Naik, and Green (2004) find specific times that leave a new venture more vulnerable to information about technological progress, and other times less so.

iii) Effect of Other Covariates

The statistically significant and positive 'overlap' indicator variable allows us to conclude that frequently-innovating companies show consistently higher returns across the entire event window than companies that only possess one innovative molecule in this dataset.

'Quarterly time trend' allows for some seasonality to be observed. Across the domestic datasets, the indicator variable is statistically significant, large, and negative, meaning that returns diminish in later business quarters. Both statistically significant variables 'quarterly time trend' and 'overlap' introduce heterogeneous effects on pharmaceutical innovation timing and frequency, respectively, nd require further research to more concretely define timing trends of such announcements.

R_m-R_f is a variable that accounts for systematic risk relative to the market. Across primary patent application datasets, this variable is negative, meaning that securities *i* are less risky relative to the market. In primary patent publication datasets, however, this variable is positive, showing more risk relative to the market.

SMB is a usually positive variable that controls for size. However, in this analysis, large companies are only included due to the earlier discussed effect of biotech clustering causing a "small firm effect" in which smaller firms tend to outperform larger ones. In the case of patent publication, large firms seem to be discounted due to inefficiency and high costs. HML accounts for the spread. This is positive because all companies included are value stocks, not unknown growth companies. The data show that portfolio returns can be accredited to this premium and therefore coefficients for HML are largely negative.

It is important to note that the lack of statistical significance in covariates R_m-R_f, SMB, and HML in multiple tables result from the small sample size and therefore lack of economical power, particularly in the CAPM and dataset that extends the analysis to FDA approval dates.

iv) International Extension

Appendix 3 depicts an international extension of analysis surrounding patent application and publication dates using both the CAPM and the Fama-French model. The effect of the pharmaceutical announcements are inconsistent with the domestic analysis of pharmaceutical firms, yielding significant negative coefficients on both patent application and publication date, which thus validates Griffin's finding (2004) that the CAPM and Fama and French's model perform optimally when localized.

v) FDA Approval Extension

Appendix 4 shows that the effect of FDA approval of a CNS drug on a firm's returns is not statistically significant. However, it is worth noting that negative coefficients can be observed for all event indicator windows, except on the announcement date, signaling positive returns as a result of such approval. This finding is consistent with other literature (Sharma and Lacey 2004).

VIII. Implications and Conclusion

This paper examined the significance of announcement effects when pharmaceutical companies request and publish patents on active ingredients in major antidepressant and antipsychotic drugs by looking at the daily stock prices surrounding various pharmaceutical announcements. Significant increases in returns were observed in the pre-event window leading up to a drug's application date. This result allows us to reject the null hypothesis that private and public information is already incorporated in a firm's security price. In the case of patent application date for CNS pharmaceuticals, the market is inefficient and returns fluctuate as a result of new information.

Patent publication announcements yield decreasing returns in the pre-event window. This validates the CAPM relationship identified by Berk, Naik, and Green (2004), who outline the decreasing risk new technologies experience as they approach completion, thereby simultaneously exhibiting decreasing returns. In the case of pharmaceutical patent publication date for CNS innovations, the null hypothesis that the market is strongly efficient cannot be rejected.

Despite heterogeneous and unexpected results, *Figure 1* and *Figure 2* in Section VI illustrate extreme volatility surrounding pharmaceutical patent announcement dates that demand research extensions. Such research extensions could include widening the data scope to other therapeutic classes of innovative pharmaceuticals and expanding the analysis to other event dates, furthering the implications of this paper. Implications stemming from innovative announcement studies such as this paper are extremely critical for investor strategy; pharmaceutical investors could more closely watch the pharmaceutical development process and invest money in companies that allocate more money to R&D as specific firms near patent application dates. Market strategists can also benefit from the findings of this paper by

potentially altering or protecting patent application announcements to ultimately maximize profits.

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Appendix 1. Capital Asset Pricing Model: Domestic Firms

Table 1.1: Effect of Patent Application on Firms' Daily Annualized Returns

Domestic Firms Traded on NYSE or NASDAQ: CAPM							
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
m-Rf	-7.40	-7.32	-7.36	-8.00	-9.00	-7.91	-8.18
	[9.29]	[9.29]	[9.29]	[9.28]	[9.03]	[9.27]	[9.25]
MB	-	-	-	-	-	-	-
ML	-	-	-	-	-	-	-
wo Weeks Before	78.94						
ay Before	[39.87]**	269.88					
ay		[158.25]*	-19.25				
ay After			[131.33]	104.51			
wo Weeks After				[151.30]	38.83		
hree Day Window					[40.02]	117.17	
ve Day Window						[86.13]	142.87
							[69.47]**
verlap	251.03	174.95	176.33	177.59	160.03	176.40	181.73
	[101.42]**	[93.95]*	[94.06]*	[93.91]*	[92.45]*	[93.81]*	[93.78]*
uarterly Time Trend	-169.67	-168.13	-168.13	-167.53	-168.42	-167.52	-167.89
	[72.06]**	[72.08]**	[[72.08]**	[72.11]**	[71.99]**	[72.12]**	[72.05]**
onstant	1263.86	1262.86	1264.04	1267.08	1260.39	1266.09	1267.13
	[221.58]***	[221.69]***	[221.67]***	[221.78]***	[221.04]***	[221.79]***	[221.58]***
olecule FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
bservations	7978	7978	7978	8009	8412	8009	8040
-squared	0.0390	0.0389	0.0385	0.0384	0.0391	0.0386	0.0389

obust standard errors in brackets, clustered by molecule,
***significant at 10%; **significant at 5%; *significant at1%

Table 1.2: Effect of Patent Publication on Firms' Daily Annualized Returns

Domestic Firms Traded on NYSE or NASDAQ: CAPM							
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
m-Rf	3.14	3.13	3.13	3.14	3.16	3.13	3.13
	[0.13]***	[0.13]***	[0.13]***	[0.13]***	[0.13]***	[0.13]***	[0.13]***
MB	-	-	-	-		-	-
ML	-	-	-	-		-	-
wo Weeks Before	-197.46						
ay Before	[89.20]**	-453.09					
ay		[350.96]	-671.87				
ay After			[320.40]**	120.78			
wo Weeks After				[346.29]	-79.15		
ree Day Window					[90.40]	-337.85	
ve Day Window						[199.61]*	-379.64
							[150.41]**
uarterly Time Trend	-159.51	-154.58	-154.77	-148.30	-116.72	-150.12	-147.77
	[93.96]*	[93.91]*	[93.89]*	[93.86]	[92.00]	[93.71]	[93.53]
onstant	1975.20	1959.85	1961.74	1940.53	1837.50	1948.36	1940.75
	[240.76]***	[240.60]***	[240.59]***	[240.38]***	[233.63]***	[240.03]***	[239.45]***
olecule FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
bservations	8530	8530	8530	8564	9006	8564	8598
-squared	0.1685	0.1682	0.1684	0.168	0.1699	0.1683	0.1688

obust standard errors in brackets, clustered by molecule

*significant at 10%; **significant at 5%; *significant at 1%

Appendix 2. Fama French Model: Domestic Firms

Table 2.1: Effect of Patent Application Event Date on Firms' Daily Annualized Returns

Domestic Firms Traded on NYSE or NASDAQ: Fama-French Model							
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
m-Rf	-4.73	-4.75	-4.81	-6.35	-7.89	-6.24	-6.52
	[11.92]	[11.93]	[11.94]	[11.92]	[11.50]	[11.91]	[11.89]
MB	14.06	14.18	14.55	14.02	14.14	13.76	14.92
	[18.39]	[18.40]	[18.39]	[18.38]	[17.79]	[18.38]	[18.36]
ML	5.02	4.75	4.68	2.32	0.83	2.44	2.23
	[22.12]	[22.13]	[22.14]	[22.09]	[21.53]	[22.08]	[22.06]
wo Weeks Before	78.5						
ay Before	[39.86]**	268.45					
ay		[158.42]*	-20.35				
ay After			[131.61]	105.5			
wo Weeks After				[151.33]	39.38		
ree Day Window					[40.02]	181.81	
ve Day Window						[86.21]	142.46
							[69.49]**
verlap	255.53	179.99	181.55	183.13	165.75	181.81	187.71
	[101.81]**	[94.42]*	[94.53]*	[94.38]*	[92.87]*	[94.28]	[94.25]
uarterly Time Trend	-170.13	-168.6	-168.63	-168.03	-168.94	-168.02	-168.43
	[72.06]**	[72.09]**	[72.08]**	[72.11]**	[71.98]**	[72.11]**	[72.05]**
onstant	1264.64	1263.68	1264.88	1268.02	1261.43	1267.01	1268.17
	[221.60]***	[221.71]***	[221.69]***	[221.77]***	[221.02]***	[221.79]***	[221.57]***
olecule FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
bservations	7978	7078	7978	8009	8412	8009	8040
-squared	0.0391	0.039	0.0386	0.0385	0.0392	0.0387	0.0389

obust standard errors in brackets, clustered by molecule

*significant at 10%; **significant at 5%; *significant at 1%

Table 2.2: Effect of Patent Publication on Firms' Daily Annualized Returns

Domestic Firms Traded on NYSE or NASDAQ: Fama-French Model							
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
:m-Rf	2.63	2.63	2.62	2.63	2.63	2.63	2.63
	[0.15]***	[0.15]***	[0.15]***	[0.15]***	[0.14]***	[0.15]***	[0.14]***
:MB	-386.65	-386.31	-386.07	-387.73	-399.44	-387.41	-390.22
	[40.05]***	[40.04]***	[40.05]***	[40.02]***	[39.28]***	[39.99]***	[39.94]***
:ML	-285.19	-285.85	-285.94	-283.48	-298.26	-283.69	-280.98
	[45.08]***	[45.07]***	[45.06]***	[45.01]***	[44.09]***	[44.99]***	[44.91]***
'wo Weeks Before	-195.63						
)ay Before	[88.68]**	-450.14					
)ay		[360.91]	-661.3				
)ay After			[316.13]**	127.71			
'wo Weeks After				[344.70]	-77.75		
'hree Day Window					[88.96]	-330.94	
'ive Day Window						[200.50]	-376.83
							[149.60]**
)uarterly Time Trend	-322.28	-317.46	-317.6	-311.53	-287.72	-313.3	-311.01
	[137.95]**	[137.99]**	[137.94]**	[137.72]**	[138.56]**	[137.60]**	[137.32]**
:onstant	2270.36	2255.36	2257.16	2237.04	2149.7	2244.77	2236.48
	[268.06]***	[267.95]***	[267.89]***	[267.44]***	[261.62]***	[267.18]***	[266.53]***
Molecule FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
)bservations	8523	8523	8523	8557	8999	8557	8591
:-squared	0.1814	0.1811	0.1813	0.1808	0.1835	0.1811	0.1817

.obust standard errors in brackets, clustered by molecule
**significant at 10%; **significant at 5%; *significant at1%

Appendix 3. International Extension

Table 3.1: Effect of Patent Application on Firms' Daily Annualized Returns

Domestic and International Firms: CAPM							
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Rm-Rf	121.19	121.24	121.27	121.44	125.44	121.47	121.52
	[5.48]***	[5.49]***	[5.49]***	[5.48]***	[5.33]***	[5.48]***	[5.46]***
SMB	-	-	-	-	-	-	-
HML	-	-	-	-	-	-	-
Two Weeks Before	12.95						
Day Before	[20.29]	9.59					
Day		[73.79]	-118.85				
Day After			[55.57]**	-37.55			
Two Weeks After				[71.66]	-1.58		
Three Day Window					[19.65]	-49.73	
Five Day Window						[39.41]	-17.69
							[32.47}
Overlap	294.01	294.16	294.26	293.97	27.58	294.06	291.47
	[88.02]**	[88.01]**	[87.99]**	[87.74]**	[36.01]	[87.76]**	[87.43]**
Quarterly Time Trend	67.99	67.99	67.99	68.18	73.34	68.18	67.24
	[88.02]**	[34.10]**	[34.09]**	[33.99]**	[33.31]**	[34.02]**	[33.89]**
Constant	-22.83	-22.10	-21.60	-23.62	-43.25	-23.18	-20.83
	[115.61]	[115.60]	[115.53]	[115.20]	[112.27]	[115.30]	[114.87]
Molecule FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	10183	10183	10183	102227	10799	10227	10271
R-squared	0.1075	0.1075	0.1077	0.1074	0.1088	0.1075	0.1077

Robust standard errors in brackets, clustered by molecule

***significant at 10%; **significant at 5%; *significant at 1%

Table 3.2: Effect of Patent Application on Firms' Daily Annualized Returns

Domestic and International Firms: Fama-French Model							
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Rm-Rf	113.46	113.56	113.55	113.81	116.61	113.81	114.00
	[6.30]***	[6.30]***	[6.30]***	[6.29]***	[6.11]***	[6.29]***	[6.26]***
SMB	-76.47	-76.41	-76.25	-76.65	-78.93	-76.55	-76.60
	[10.15]***	[10.15]***	[10.15]***	[10.13]***	[9.95]***	[10.13]***	[10.10]***
HML	-15.37	-15.26	-15.38	-14.99	-17.89	-15.06	-14.75
	[12.25]	[12.25]	[12.25]	[12.22]	[11.87]	[12.22]	[12.19]
Two Weeks Before	14.32						
Day Before	[20.15]	13.13					
Day		[72.43]	-110.57				
Day After			[56.52]**	-30.58			
Two Weeks After				[71.00]	0.91		
Three Day Window					[19.54]	-43.38	
Five Day Window						[39.15]	-12.63
							[32.33]
Overlap	283.09	283.25	283.38	282.53	15.42	282.62	280.53
	[87.63]**	[87.62]**	[87.60]**	[87.33]**	[35.87]	[87.34]**	[87.01]**
Quarterly Time Trend	67.53	67.53	67.53	67.60	73.98	67.61	66.89
	[33.98]**	[33.98]**	[33.98]**	[33.87]**	[33.28]**	[33.90]**	[33.76]**
Constant	-18.31	-17.50	-17.04	-18.49	-42.61	-18.11	-16.51
	[115.24]	[115.22]	[115.18]	[114.80]	[112.15]	[114.90]	114.56
Molecule FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	10183	10183	10183	10227	10799	10227	10271
R-squared	0.1141	0.114	0.1142	0.114	0.1157	0.1141	0.1143

Robust standard errors in brackets, clustered by molecule

***significant at 10%; **significant at 5%; *significant at 1%

Table 3.3: Effect of Patent Publication Event Date on Firms' Daily Annualized Returns

Domestic and International Firms: CAPM							
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Rm-Rf	2.89	2.89	2.89	2.89	2.90	2.89	2.89
	[0.12]***	[0.12]***	[0.12]***	[0.12]***	[0.12]***	[0.12]***	[0.12]***
SMB	-	-	-	-	-	-	-
HML	-	-	-	-	-	-	-
Two Weeks Before	-142.55						
Day Before	[82.25]*	36.54					
Day		[337.19]	-384.85				
Day After			[302.22]	-30.23			
Two Weeks After				[336.79]	-77.35		
Three Day Window					[82.66]	-127.24	
Five Day Window						[189.50]	-211.28
							[141.67]
Quarterly Time	1052.33	1052.33	1052.33	1052.71	1101.82	1052.71	1053.35
	[106.18]***	[106.18]***	[106.20]***	[105.98]****	[103.31[***	[105.96]***	[105.62]**
Constant	811.74	802.82	805.14	794.00	674.13	795.81	787.96
	[246.95]***	[247.00]***	[246.92]***	[246.54]***	[239.36]***	[246.45]***	[245.72]**
Molecule FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	11546	11546	11546	11592	12190	11592	11638
R-squared	0.1506	0.1504	0.1505	0.1499	0.1513	0.1499	0.1505

Robust standard errors in brackets, clustered by molecule

***significant at 10%; **significant at 5%; *significant at 1%

Table 3.4: Effect of Patent Publication Event Date on Firms' Daily Annualized Returns

Domestic and International Firms: Fama-French Model							
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Rm-Rf	2.58	2.58	2.58	2.58	2.60	2.58	2.58
	[0.12]***	[0.12]***	[0.12]***	[0.13]***	[0.13]***	[0.13]***	[0.13]***
SMB	-206.69	-206.74	-206.79	-207.61	-220.03	-207.66	-208.69
	[33.24]***	[33.25]***	[33.24]***	[35.66]***	[34.87]***	[35.65]***	[35.55]***
HML	-216.24	-217.27	-217.74	-212.35	-205.28	-212.53	-211.07
	[34.45]***	[34.45]***	[34.45]***	[37.91]***	[37.16]***	[37.91]***	[37.84]***
Two Weeks Before	-133.47						
Day Before	[82.02]*	38.98					
Day		[308.63]	-401.84				
Day After			[308.64]	-38.35			
Two Weeks After				[339.88]	-75.03		
Three Day Window					[82.41]	-134.73	
Five Day Window						[190.68]	-217.32
							[142.36]
Quarterly Time	1054.47	1054.46	1054.45	1054.29	1103.13	1054.28	1054.92
	[93.23]***	[93.24]***	[93.23]***	[107.98]***	[105.16]***	[107.95]***	[107.61]***
Constant	889.55	881.49	884.07	872.64	752.08	874.58	866.48
	[211.42]***	[211.39]***	[211.38]***	[251.75]***	[244.01]***	[251.67]***	[250.92]***
Molecule FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	11539	11539	11539	11.585	12183	11585	11631
R-squared	0.1556	0.1554	0.1556	0.1548	0.1564	0.1549	0.1554

Robust standard errors in brackets, clustered by molecule
***significant at 10%; **significant at 5%; *significant at 1%

Appendix 4. FDA Approval Extension

Table 4.1: Effect of FDA Drug Approval on Firms' Daily Annualized Returns

Domestic and International Firms: CAPM							
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Rm-Rf	98.29	98.33	98.13	98.26	99.13	98.31	98.06
	[10.90]***	[10.91]***	[10.91]***	[10.90]***	[10.76]***	[10.91]***	[10.90]***
SMB	-	-	-	-	-	-	-
HML	-	-	-	-	-	-	-
Two Weeks Before	23.86						
Day Before	[41.70]	-123.64					
Day		[133.74]	89.74				
Day After			[182.58]	-159.58			
Two Weeks After				[149.58]	40.45		
Three Day Window					[44.71]	-64.75	
Five Day Window						[93.29]	17.82
							[70.98]
Quarterly Time Trend	189.74	188.27	188.91	182.12	179.06	182.01	177.58
	[58.91]**	[58.75]***	[58.79]***	[58.73]***	[56.31]***	[58.67]***	[58.49]***
Constant	529.35	534.21	532.08	545.50	537.79	545.84	553.16
	[108.04]***	[107.59]***	[107.60]***	[107.56]***	[103.10]***	[107.49]***	[107.12]***
Molecule FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	2140	2140	2140	2149	2266	2149	2158
R-squared	0.2128	0.2129	0.2128	0.2134	0.2091	0.2132	0.2126

Robust standard errors in brackets, clustered by molecule

***significant at 10%; **significant at 5%; *significant at 1%

Table 4.2: Effect of FDA Drug Approval on Event Date on Firms' Daily Annualized Returns

Domestic and International Firms: Fama-French Model							
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Rm-Rf	113.25	113.50	113.09	113.40	114.18	113.65	113.60
	[11.64]***	[11.63]***	[11.64]***	[11.63]***	[11.53]***	[11.65]***	[11.65]***
SMB	-26.61	-26.70	-26.48	-26.53	-24.36	-26.50	-26.29
	[18.20]	[18.20]	[18.22]	[18.16]	[17.98]	[18.17]	[18.14]
HML	70.59	71.78	70.58	71.93	71.20	72.98	74.19
	[23.38]***	[23.44]***	[23.39]***	[23.35]***	[23.01]***	[23.38]***	[23.32]***
Two Weeks Before	23.06						
Day Before	[41.70]	-151.10					
Day		[126.79]	81.74				
Day After			[185.25]	-144.86			
Two Weeks After				[146.22]	40.86		
Three Day Window					[44.73]	-71.93	
Five Day Window						[92.16]	9.75
							[58.32]
Quarterly Time Trend	191.53	190.06	190.73	183.98	182.14	183.81	179.68
	[58.75]***	[58.56]***	[58.62]***	[58.57]***	[56.19]***	[58.53]***	[58.32]***
Constant	521.96	526.82	524.64	183.98	528.78	538.51	545.41
	[107.57]***	[107.07}***	[107.13]***	[58.57]***	[102.76]***	[107.05]***	[106.64]***
Molecule FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	2140	2140	2140	2149	2266	2149	2158
R-squared	0.2172	0.2174	0.2172	0.2179	0.2134	0.2187	0.2173

Robust standard errors in brackets, clustered by molecule

***significant at 10%; **significant at 5%; *significant at 1%