2019

TMI : an examination of excess returns surrounding phase III FDA approvals

Luke Chiotelis

TMI: An Examination of Excess Returns Surrounding Phase III FDA Approvals

by

Luke Chiotelis

Honors Thesis

Submitted to:

Economics Department

University of Richmond

Richmond, VA

May 1, 2019

Advisor: Dr. Cassandra Marshall

1. Introduction

Over the past three decades, the Biotechnology and Pharmaceutical industry has had the largest growth rate of any sector in the U.S. economy. Currently, the largest 10 companies have a market cap of over 700 billion dollars. In the past 20 years, Biotech has outperformed the Standard and Poor's 500 index earning superior returns for those willing to invest in this risky, high growth industry (Bloomberg L.P.). This upward trend is expected to continue as both institutional and private investment in biotech continues to soar.

The Pharmaceutical and Biotechnology industries function uniquely due to their high level of regulation. The government, more specifically the Food and Drug Administration (FDA), has a direct impact on the success of a pharmaceutical company. Before a drug can be taken to market it must first pass the three phases of FDA approval: Phase I, Phase II, and Phase III.

Phase I consists of a sample of 20 to 200 patients and is used to determine whether or not the drug is safe for human consumption (Office of the Commissioner). It uses ascending nonclinical doses administered by a clinical researcher on primarily healthy patients (Office of the Commissioner). Approximately 70% of applications make it through this stage (Office of the Commissioner). Phase II has a larger sample of 100 to 300 patients who are administered a therapeutic level dose of the drug, again by a clinical researcher (Office of the Commissioner). In this phase, the researcher is testing for the drug's efficacy and side effects, by testing on patients with specific health conditions (Office of the Commissioner). Only 33% of drugs make it through Phase II testing (Office of the Commissioner). In Phase III it is assumed that the drug is effective and must be tested on a wider scale of 300 to 3000 patients. Approximately only

25% of drugs that enter Phase III are ultimately approved and can be taken to market (Office of the Commissioner).

Getting a drug approved is extremely expensive, often costing up to 2.6 billion dollars (Dimasi 2006). According to the FDA's own estimate only about six out of 100 drugs that enter Phase I will ultimately be approved. Given the high upfront capital expenditure and the uncertainty of future cash flows it is difficult to understand why a company would undertake such a herculean effort. Simply put, the prospect of bringing a new drug to market is exciting. A successful drug is a potentially massive source of income for its creator. A new banner drug like Humira, Viagra, or Crestor could have a lifetime revenue in the hundreds of billions.

Pharma and Biotech are big business and Wall Street knows this; however, due to this high degree of uncertainty, the market has a difficult time effectively pricing this class of stock. A successful Phase III approval can double a company's market cap. Spark Therapeutics stock price more than doubled from $50 to $113 in February of 2019 with the approval of its banner drug (see Attachment 1). A failure, however, can be catastrophic. Biogen, a large pharmaceutical company saw its market capitalization[1] fall by over a third (see Attachment 2) in the March of 2019. Across both approval and rejection events, those who trade equities saw the potential for massive gains.

The largest insider trading scandal in the history of the stock market surrounded a biotechnology approval. Steven Cohen and his firm SAC Capital were long[2] 700 million dollars on Elan, an Irish biotechnology company (Keefe 2017). Elan had submitted the most exciting

---

[1] Market Capitalization- Value in totality of a company's ownership shares outstanding

[2] Long- to be long means to own and thus bet on the value of a company's stock to rise.

Alzheimer's drug of all time. Alzheimer's has no cure and is famously difficult to treat. Bringing a viable Alzheimer's drug to market would be a veritable gold mine. When the firm underhandedly learned of the drugs upcoming disappointing results, they not only liquidated, but also reversed their position. They shorted[3] the company's stock, and made an illegal profit of 275 million dollars (Keefe 2017).

A better understanding of the FDA approval process and the way a company's stock price fluctuates in the time surrounding approvals can yield practitioners a unique advantage in their pursuit of profits. I hypothesize that biotechnology and pharmaceutical companies return data surrounding Phase III FDA approvals will mimic the announcement effects traditionally surrounding quarterly earnings. I also predict that less transparent firms will experience greater cumulative abnormal returns, yielding negative and significant coefficients on all three transparency measures: press releases one year prior to approval, analyst coverage, and the cumulative abnormal return associated with the firm's regular quarterly earnings announcements.

The rest of the paper proceeds as follows: Section 2 provides a summary of the theory and literature review, Section 3 describes the data, Section 4 analyzes the data and explains the results, and Section 5 concludes.

2. Theory and Literature Review

The efficient market hypothesis states that markets are "efficient", meaning that market prices fully reflect all available information (Fama 1970). The price of a stock should reflect the expected future value of the firm's cash flows. In this framework, there are two types of risk:

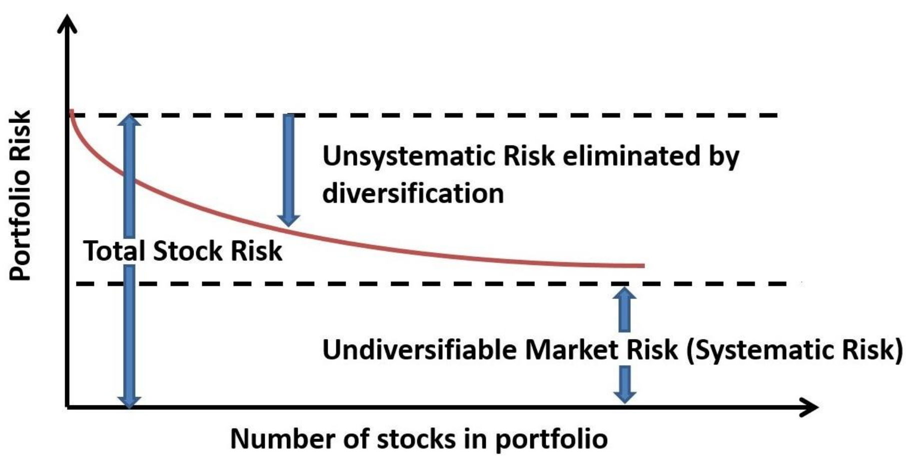
[3] Short- to short means to bet against, and thus yield profit when a company's share price falls

unsystematic risk and systematic risk. Unsystematic risk, also known as specific risk, is the risk associated with owning a specific security or investing in a specific industry. Imagine a hypothetical individual whose entire portfolio consisted of one security, say Boeing. Given its recent aircraft failures, Boeing saw a massive drop in stock price. Holding any one security exposes the owner to that securities unsystematic risk. Imagine if rather than investing solely in Boeing the hypothetical individual owned the stock of many companies in his portfolio. The individual would be less exposed to the drop in Boeing's stock price. The more stocks an individual's portfolio the lower the unsystematic risk of the portfolio. In an efficient market, all unsystematic risk can be effectively eliminated via diversification. Systematic risk, also known as market risk, is the uncertainty inherent in putting one's money in the market. All stocks that are traded are subject to changes in price when there are broad market movements. The measure of a stock's responsiveness to the market is called its beta. The risk of a portfolio can be lowered to solely its systematic risk through diversification[4].

This idea gave birth to capital asset pricing. Capital asset pricing theory aims to model the expected returns of given securities. According to this theory because unsystematic risk

---

4



can be eliminated via portfolio construction, the only risk a shareholder must be compensated for is systematic risk. By controlling for the factor of the market and adjusting for the current risk-free rate of return[5], it is possible to measure expected returns (Sharpe 1964). The first and least restrictive model is the Market Model:

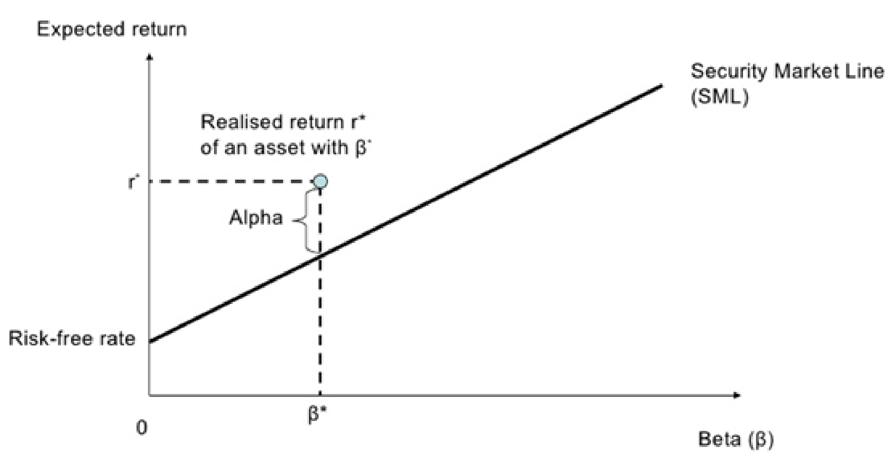
$$r_i = r_f + \beta_1 \ (r_m - r_f)$$

r_i : Expected Return on a given security
r_f : Risk-free rate
r_m : Return on the market

This model is able to predict the return on a specific security. This was the prevailing theory for many years and by its virtue practitioners were able to create the security market line[6] and determine return for any given stock given its beta. The model had an issue, stocks were earning return in excess of risk. Return in excess of predicted risk is called alpha[6] and in an efficient market this should not exist. Efficient market theorists believe that it is impossible to beat the market and that any excess return must be due to some unseen risk.

[5] The primary metric for estimating the risk free rate is the yield on 10 year treasury strips. Currently it is approximately 2.5%.

[6]



27

In 1993 Eugene Fama and Kenneth French pioneered the Fama French Three Factor Model:

$$r_i = r_f + \beta_1 (r_m - r_f) + \beta_2 (SMB) + \beta_3 (HML) + \varepsilon$$

r_i : Expected Return on a given security
r_f : Risk-free rate
r_m : Return on the market
SMB: Size Premium, returns small cap minus large cap companies
HML: book to market premium, High book to market minus low book to market

This model adds two new risk factors small minus big and high book to market minus low book to market. This model assumes that smaller cap companies are inherently riskier than larger cap companies and that companies with higher book to market are intrinsically less risky than low book to market companies. This model controls for size and book to market value. Proponents of the efficient market hypothesis argue that those factors represent risk factors that must be accounted for when estimating the price of a stock (Fama 1993). Theoretically, this variation of the CAPM should, with higher accuracy, predict the price of any given stock. This model was the standard until it was updated to include a fourth factor for momentum:

$$r_i = r_f + \beta_1 (r_m - r_f) + \beta_2 (SMB) + \beta_3 (HML) + \beta_4 (Momentum) + \varepsilon$$

r_i : Expected Return on a given security
r_f : Risk free rate
r_m : Return on the market
SMB: Size Premium, returns small cap minus large cap companies
HML: book to market premium, High book to market minus low book to market
Momentum: Current trend upward or downward

Momentum describes the propensity of a company's stock price to continue rising if it is going up and to continue declining if it is going down. This is the final and most restrictive model. Examining the difference between expected returns as predicted by these models and actual daily returns yields a value for cumulative abnormal returns (CAR) (Brown 1985). The time leading up to and surrounding an event yields robust data for the effect of that event on the price of a security.

The efficient market hypothesis is widely accepted; however, some of its key assumptions are not met when applied to Pharmaceutical and Biotechnology companies. In order for efficiency to hold, not only must all knowledge be widely disseminated, but it also must be scrutable to those who receive it. While much Pharmaceutical and Biotechnology data is publicly available, it requires expert knowledge to understand, such that it is useless to the general public due to information complexity (Janney 2003). This creates systematic inefficiencies in the market due to the complexity of the information.

Not only private individuals fall victim to this knowledge gap; it is estimated that anywhere from 35% to 40% of all publicly traded companies have no analysts assigned to cover them. This dearth of coverage means that these innovative, high growth potential companies are often not understood, even by institutional investors (Canviet 2010). This misalignment of value is further driven by the ambiguity as to the effectiveness of the drug being developed and the uncertainty of the FDA approval process. Many of these companies do not expect to have cash flows of any kind for, in some cases, many years. Investments in this class of companies are speculative and thus riddled with predictable irrational market behaviors. With a better understanding of these market concepts, it is possible to net high abnormal returns in excess of risk.

Examinations of announcement effects have long been examined in both finance and economics literature. Early studies focused primarily on the impact of major financial announcements like the establishment of a dividend or a firm's regular quarterly earnings announcements. One of the earliest papers that measured announcement effects associated with earnings was published by William H. Beaver (1968). In his paper, he challenges Miller and Modigliani's (1963) assertions that firm announcements about earnings lack informational value because there are often major measurement errors and other indicators convey firm performance in a timelier manner. At the time, the prevailing wisdom was that the market would have already processed that information and reflected it in its share price.

This assertion implies that earnings reports convey little the market does not already know, and thus should not affect the price of a company's securities. His data set included 143 firms traded on the New York Stock Exchange with a total of 506 earnings announcements. He measured the stocks over a 17 week period surrounding the announcement with week t=0 being the week of the announcement and weeks t= -8 and t= +8 the eighth week directly preceding and following, respectively. Beaver found that in week t=0 the volume of trading increased, as did price volatility. This effect was coupled with decreased activity in weeks -8 through -1 and increased activity in week +1 through week +8. During week zero and the weeks immediately following, the market violated "semi-strong efficiency" and abnormal returns were realized. These types of abnormal returns surrounding earnings announcements have been corroborated in both the United States and abroad and have remained congruent over time

(Landsman and Maydew 2002, Oopong 1995, Syed 2017). Similar results are also exhibited surrounding announcements regarding dividends and special dividends across firms both domestic and abroad (Dewentner 1998).

Financial disclosures are not the only important announcements for Pharmaceutical and Biotechnology companies. FDA approval is an important step in the life cycle of these firms. Rothenstien et. al (2011) examined the effect of Phase 3 FDA approval on the stock prices. They examined 109 FDA trials and regulatory decisions. They found that the average price of a stock in the 4-month period rose 13.7% prior to a positive release. Announcement effects are seemingly present even before the announcement is made. Similar findings show that the market largely overreacts post-release. Salil Sarkar and Pieter Jong (2006) find in an analysis of 189 firms that markets respond positively when the FDA approves a drug and negatively when the FDA signals negatively. This effect has a greater magnitude for negative information. This aligns with research on investor psychology (Wilcox 1998).

Similar results were noted by Thomas Hwang (2013) in a smaller data set of 24 regulatory decisions across all phases. His sample was primarily large U.S. Biotechnology companies with drugs in the Oncology and Neurology space. Hwang found positive and significant abnormal returns surrounding positives decisions and negative significant abnormal within a two-day window of the event. His paper differed in that he found that abnormal returns did not differ significantly by triall phase. Congruent with previous research, it was determined that negative overreactions were of greater magnitude than positive overreactions. Hwang's assertions were corroborated by Anurag Sharma (2014), with a larger sample and a longer event window of 21 days.

Transparency should lower cumulative abnormal returns. The efficient market hypothesis states that market prices reflect all available information (Fama 1970). The more information that is publicly available the more able the market should be to appropriately price the stock. The more information put out by firm the more likely it is that the trading price will reflect the true value. This decreases the likelihood of cumulative abnormal returns.

3. Data

The data for this study was collected from many sources. The sample consisted of 260 Phase III approvals from 150 companies from 2009 to 2018. To collect this data I gathered approval dates and company names and stock tickers from the FDA Orange Book and Biopharmcatalyst.com. With the dates and tickers, I was able to use the Wharton Data Research services to pull the cumulative abnormal returns surrounding each approval. For this estimation, the online research tool tracked the trading history of each company's stock for 100 days to "estimate the expected return and residual return variance" (*Wharton Research Data Services*). The sample consisted of companies with 70 valid trading days within this 100-day window. The program uses a 50 trading day gap between the tracking period and the estimation period. This limits the "likelihood that the risk model estimation is affected by the event-induced return variance" (*Wharton Research Data Services*). For this study two estimation windows were used, a three day window (one day prior to and one day after the approval, which will be referred to as -1, +1) and a seven day window (three days prior to and three days after the approval, which will be referred to as -3, +3). The data service then automatically calculates the expected return using various asset pricing models. This paper will focus on the least restrictive, the Market Model, and the most restrictive, the Fama French Plus

Momentum Model. Then the data service subtracts then subtracts the expected return from the actual return experienced in the estimation window. This value is the cumulative abnormal returns. I then took the absolute value of the Cumulative abnormal return to measure the absolute degree of the change independent of direction and winsorized[7] the highest five percent of the sample

I used three variables as a proxy for transparency: company press release made within the year to The Phase III announcement, number of analysts covering[8] the stock at the time of approval, and the absolute value of the average cumulative abnormal return surrounding the four quarterly earnings announcements made prior to the Phase III announcement. The Security and Exchange Commission mandates all publicly traded companies report both quarterly (using a 10-K form) and yearly (using a 10-Q form) to report the status of the business. Firms can opt to use a press release (using an 8-K) form to report additional information. The more transparent the firm the greater number of 8-Ks it will file. I predicted that the beta associated with press releases would be negative and significant.

I used the number of analyst covering a firm at the time of announcement. Coverage Studies in the past have used this metric as a measure of information asymmetry[9] (Chang 2006). There is strong evidence supporting the notion that the number of analysts covering a firm is negatively correlated with the information asymmetry of a given firm (Chang 2006). The

---

[7] Winsorize- to eliminate outliers and replace them with the observations closest to them (Hargrave 2018). This is done to limit the effect of abnormal extreme values, or outliers, on the calculation (Hargrave 2018).
[8] Analyst Coverage- A stock is covered when sell-side analyst publishes research reports and investment recommendations for clients.
[9] Information Asymmetry- information relating to a transaction in which one party has relevant information that is not known by or available to the other party

more analyst covering a firm, the more information there should be available on that firm, increasing transparency. This was collected using the Analyst recommendation function on Bloomberg. This page displays research analysis from each analyst covering a firm. For each company in the data set I counted the number of analysts that covered the stock on the approval date. I predicted that the beta associated with analyst coverage would be negative and significant.

The final metric used for transparency was the cumulative abnormal returns surrounding a firms quarterly earnings announcements. These quarterly announcements often contain major business updates. Large price reactions surrounding quarterly earning imply reports that are highly informative. I hypothesized that the more information that exists about a firm the more effectively it can be priced and thus the less likely you are to pick up cumulative abnormal returns in the future surrounding the Phase III announcement. To collect this data I used the COMPUSTAT data set and the previously gathered company tickers and found the quarterly earnings announcement dates. Next, I ran 4 WRDS event studies for each earnings announcement one year prior to approval. It was necessary to match the window of the dependent variable to the window of the independent variable; as such, it was necessary to have estimates for both window lengths across both models (Market and Fama French Plus Momentum Model). Then, I averaged the absolute value of the four for a single cumulative abnormal return value. All three transparency measures were winsorized.

From COMPUSTAT I also collected values for each company's total assets, capital expenditures, earnings per share, net income, operating income after depreciation, in-process research and development, and sales, all of which were winsorized (see Table One for variable names and descriptions). The average firm in the sample has \$29.34 million in assets, \$7.25 million in sales annually, and earns a net income of \$1.29 million per year (See Table Two for descriptive statistics on all key variables).

4. Results

Table Three is a correlation matrix for all key variables. The correlation matrix revealed interesting significant correlations between the return variables and the transparency variables: analyst coverage, press releases, and the cumulative abnormal returns surrounding earnings announcements. I hypothesize that there would be significant and negative coefficients on all transparency variables.

Table Four shows results of all OLS regressions using -1, +1 Market Model cumulative abnormal returns. The first condition regressed Market Model cumulative abnormal returns against the natural log of analyst coverage:

$$1)\quad \text{MM } +1,-1 \text{ CAR} = \alpha + \beta_1 \text{ (Ln Coverage)} + \mu$$

This yielded a negative and significant beta value of -0.035 ($p<0.01$). This means that as analyst coverage increases by one percent the cumulative abnormal returns should be lowered by 0.035%. While this may seem small in magnitude given the potentially large size of investments an increased return of 0.035% can yield large monetary rewards in excess of risk. Then, I regressed the same dependent variable against the natural log of press releases:

$$2)\ \text{MM } -1, +1 \text{ CAR} = \alpha + \beta_1 \text{ (Ln 8-Ks)} + \mu$$

This yielded a non-significant negative coefficient of -0.012 which is consistent with its predicted direction. Next, I used both regressors in a combined test:

$$3)\ \text{MM } -1, +1 \text{ CAR} = \alpha + \beta_1 \text{ (Ln Coverage)} + \beta_2 \text{ (Ln 8-Ks)} + \mu$$

This yielded a -0.034 ($p<0.01$) beta for coverage and a negative non-significant beta of -0.010 for the number of press releases.

For robustness and to see if the effect diminished I extended the estimation window to -3, +3 (see Table Five). Not only did the effect persist but it became more pronounced (Table Four shows results of all OLS regressions using -3, +3 Market Model cumulative abnormal returns). I first regressed the wider window Market Model cumulative abnormal returns against the natural log of analyst coverage:

$$6)\quad \text{MM -3, +3 CAR} = \alpha + \beta_1 \text{ (Ln Coverage)} + \mu$$

The magnitude of the coefficient on coverage increased -0.056 ($p<0.01$). In this larger window, a one percent increase in analyst coverage decreased cumulative abnormal returns by 0.056%. Then, I regressed the same dependent variable against the natural log of press releases:

$$7)\quad \text{MM -3, +3 CAR} = \alpha + \beta_1 \text{ (Ln 8-Ks)} + \mu$$

Again this yielded a non-significant beta, -0.017, in the direction I predicted. Next, I ran a joint test with both regressors:

$$8)\quad \text{MM -3, +3 CAR} = \alpha + \beta_1 \text{ (Ln Coverage)} + \beta_2 \text{ (Ln 8-Ks)} + \mu$$

This yielded a -0.055 ($p<0.01$) coefficient for coverage and a negative non-significant coefficient of -0.014.

The Market Model is the least restrictive model. It is possible that the magnitude of the cumulative abnormal return is lesser than is being predicted in my dependent variable and as such all of my coefficients are inherently flawed. The Market Model does not control for known risk factors such as company size, book to market ratio, or trends in stock prices. Companies that are smaller are inherently riskier as are companies with high book to market ratios and stock prices tend to demonstrate momentum in the short run. In an effort to assuage this concern I ran the same analysis with the most restrictive model, the Fama French Plus Momentum Model. Table Six shows results of all OLS regressions using -1, + Fama French Plus Model cumulative abnormal returns.

In my first regression I regressed Fama French Plus Momentum Model cumulative abnormal returns against the natural log of analyst coverage:

$$11)\ \text{FFPM } +1,-1 \text{ CAR} = \alpha + \beta_1 (\text{ Ln Coverage }) + \mu$$

This yielded a negative and significant beta value of -0.036 ($p<0.01$) greater in magnitude than the Market Model. This means that a one percent change in analyst coverage lowers cumulative abnormal returns by .036% Then, I regressed the same dependent variable against the natural log of press releases:

$$12)\ \text{FFPM } -1, +1 \text{ CAR} = \alpha + \beta_1 (\text{ Ln 8-Ks }) + \mu$$

This yielded a non-significant negative coefficient of -0.012 the direction I predicted. Next, I tested both regressors:

$$13)\ \text{FFPM } -1, +1 \text{ CAR} = \alpha + \beta_1 (\text{ Ln Coverage }) + \beta_2 (\text{ Ln 8-Ks }) + \mu$$

This yielded a -0.036 ($p<0.01$) beta for coverage and a negative non-significant beta of -0.010 for the number of press releases.

For robustness and again to see if the effect diminished I extended the estimation window to -3, +3. Table Seven shows results of all OLS regressions using -3, +3 Fama French Plus Momentum Model cumulative abnormal returns). In this condition I first regressed Fama French Plus Momentum Model cumulative abnormal returns against the natural log of analyst coverage:

$$16)\ \text{FFPM -3, +3 CAR} = \alpha + \beta_1 (\text{ Ln Coverage }) + \mu$$

The magnitude of the coefficient on coverage again increased to -0.054 ($p<0.01$). In this larger window, a one percent increase in analyst coverage decreased cumulative abnormal returns by 0.054%. Then, I regressed the same dependent variable against the natural log of press releases:

$$17)\ \text{FFPM -3, +3 CAR} = \alpha + \beta_1 (\text{ Ln 8-Ks }) + \mu$$

Again this yielded a non-significant beta, -0.021, in the direction I predicted. Next, I ran a joint test with both regressors:

$$18)\ \text{FFPM -3, +3 CAR} = \alpha + \beta_1 (\text{ Ln Coverage }) + \beta_2 (\text{ Ln 8-Ks }) + \mu$$

This yielded a -0.054 ($p<.01$) beta for coverage and a negative non-significant beta of -0.018 for the number of press releases.

Next, I aimed to quantify the effect of cumulative abnormal returns surrounding earnings announcements. I hypothesized that the beta would be significant and negative. It was my expectation that more informative quarterly earnings would cause broad movements in stock price, yielding cumulative abnormal returns surrounding these announcements. The more information available in the market prior to the Phase III approval the more informative the firm is and thus the lower cumulative abnormal surrounding the approval.

First, I used the least restrictive model, the Market Model, regressing Market Model cumulative abnormal returns surrounding earnings announcement during the prior year against cumulative abnormal returns surrounding Phase III approval (see Table Four):

$$4)\ \text{MM -1, +1 CAR} = \alpha + \beta_1 (\text{ CAR Earnings -1,+1 }) + \mu$$

This yielded a positive significant beta of 0.280 ($p<.01$). This means that a one unit change in cumulative abnormal returns surrounding earnings increased cumulative abnormal returns surrounding approval by 0.280. For robustness increased the window to -3, +3 (see Table Five):

$$9)\quad \text{MM -3, +3 CAR} = \alpha + \beta_1 \text{ (CAR Earnings -3, +3)} + \mu$$

This yielded a positive and significant coefficient of .379 ($p<0.01$).

Next, I moved to the Fama French Plus Momentum Model. I began by regressing the Fama French Plus Momentum Model cumulative abnormal returns with a -1, +1 window against cumulative abnormal returns surrounding Phase III approval (see Table Six):

$$14)\ \text{FFPM -1, +1 CAR} = \alpha + \beta_1 \text{ (CAR Earnings -1,+1)} + \mu$$

This yielded a positive significant beta of 0.283 ($p<0.01$). For robustness increased the window to -3, +3 (see Table Seven):

$$19)\ \text{FFPM -3, +3 CAR} = \alpha + \beta_1 \text{ (CAR Earnings -3, +3)} + \mu$$

This yielded a positive and significant beta of 0.365 ($p<0.01$).

In all models across all windows the variable for cumulative abnormal returns surrounding quarterly earnings announcements is added to the other transparency variables the coefficient for coverage remains negative and significant ($p<0.01$) and the coefficient on cumulative abnormal return surrounding earnings announcements remains positive and significant ($p<0.01$), while both decrease in magnitude. The beta on Press Releases was always negative and non-significant (see Tables Four, Five, Six, and Seven).

I next aimed to examine if there was a difference between firms that were highly transparent and firms that were exceptionally tight-lipped. For the rest of my analysis, I used only the -1, +1 day window cumulative abnormal returns from the Fama French Plus Momentum Model. I broke down each of my key transparency variables into above and below median (see Table Eight). Firms above median in press releases did not see significantly different cumulative abnormal returns surrounding Phase III approval. Analyst coverage, however, bore more interesting results. In both models there were significantly higher cumulative abnormal returns for firms that were above median. In the Market Model, below median analyst coverage firms averaged cumulative abnormal returns of 0.04892 and above median firms returned only 0.02684 making the difference 0.02207. To test this difference, in this condition and in all following conditions I used an independent sample T-test. This difference was statistically significant with a p-value less than 0.01 (see table 8). The same principle holds true in the more restrictive Fama French Plus Momentum Model, albeit with a lower magnitude. Below median covered firms averaged cumulative abnormal of 0.04841 and above median firms returned only 0.02690, making the difference .02151. This difference was statistically significant with a p-value less than .01. The effect of cumulative abnormal returns surrounding earnings produced opposite results. Above median firm in this category, using the Market Model saw returns averaging at 0.04753, 0.01930 greater than below median firms which saw returns of only 0.02824. The difference between the two groups was statistically significant ($p<.05$). The same was true for the Fama French Plus Momentum Model (see Table Eight).

Based on these results I created two new variables: the high transparency firm and the low transparency firm (see Table Nine). In order to qualify as low transparency the firm had to have below the median values for all three transparency measures, press releases, analyst coverage, and cumulative abnormal returns surrounding earnings (see Table Nine). Conversely, the high transparency firm was required to be above the median in all three categories. In my sample there were 12 low transparency firms and 23 high transparency firms.

Both high and low transparency firms experienced cumulative abnormal returns surrounding their Phase III announcement. The low transparency firms, on average, saw Market Model cumulative abnormal returns of 0.08418 while the high transparency firms saw cumulative abnormal returns of only 0.04868 a statistically significant difference ($p<0.05$). The returns when the Fama French Plus Momentum Model was applied also had a statistically significant difference ($p<0.05$). Low transparency firms had cumulative abnormal returns 0.07778 while high transparency firms saw returns of only 0.04759. When I added a dummy variable for least transparent firm to the full Fama French Plus Momentum Model regression it generated a positive and significant beta of 0.022 ($p<0.05$) (see Table Ten). This means that the less transparent firms typically experience greater cumulative abnormal returns.

This led me to wonder if there was a nonlinear relationship between any of the transparency measures and my cumulative abnormal return variables. First I ran a regression of Fama French Plus Momentum Model -1, +1 cumulative abnormal returns against analyst coverage and analyst coverage squared (see Table Eleven):

$$23)\ \text{FFPM -1, +1 CAR} = \alpha + \beta_1 (\text{ Ln Coverage }) + \beta_2 (\text{ Ln Coverage}^2) + \mu$$

This yielded interesting results. The sign on the beta associated with coverage switched from -0.036 ($p<0.01$) to 0.057 ($p<0.05$) and the beta on squared coverage was -0.047 ($p<0.01$). This seemingly implies a non-linear relationship. After examining the relationship further the maximum of the model peaks at firms with two covering analysts. Given that my sample has so few examples of this I feel the relationship, while interesting and plausible, may be spurious (see Chart One).

The final test I ran was an interaction between my analyst coverage variable and my quarterly earnings cumulative abnormal returns with Fama French Plus Momentum Model -1, +1 cumulative returns as the dependent variable:

$$24)\ \text{FFPM -1, +1 CAR} = \alpha + \beta_1 (\text{ Ln Coverage }) + \beta_2 (\text{ CAR Earnings -1,+1})$$

$$25)\ \text{FFPM -1, +1 CAR} = \alpha + \beta_1 (\text{ Ln Coverage }) + \beta_2 (\text{ CAR Earnings -1,+1}) + \beta_3 (\text{ Ln Coverage* CAR Earnings -1,+1}) + \mu$$

The first regression (without the interaction) bore coefficients of -0.035 on coverage ($p<0.01$) and 0.0145 on earnings ($p<0.05$) (see Table Twelve). The regression with interaction term yielded different results. The coverage beta increased in magnitude to -0.043 ($p<0.01$). The beta on quarterly earnings cumulative abnormal returns flipped signs to -0.016 and lost its significance. The interaction term had a non-significant beta of 0.155

5. Conclusions

Cumulative abnormal returns on company stocks exist from the least restrictive pricing model (the Market Model) to the most restrictive generally accepted pricing model (the Fama French Plus Momentum Model). The markets respond so positively that the returns subsist from the -1, +1 window to the -3, +3 window.

My hypothesis surrounding analyst coverage rang true. Across all models and time windows the beta associate with coverage remained significant and negative. Analyst coverage acts as an effective proxy for transparency as both retail and institutional investors follow the guidance of informed analysts. This effect is likely exacerbated, as analyst coverage is also a proxy for general institutional awareness of the firm's existence. When I examined my findings surrounding a potential nonlinear relationship between coverage and cumulative abnormal returns while potential spurious the data suggested that firms with two or less analyst covering them at the time of approval saw positive returns to an increase in analyst coverage. My sample, unfortunately, had too few examples of this class of company to derive meaningful conclusions from this enhanced model. While my sample was limited in this way it did capture the majority of Phase III approvals from 2009- 2018. Given this comprehensive makeup, I posit that the dearth of firms with 0-2 analyst covering them was a function of the rarity of the situation rather than a limitation of my sample. A firm that makes it through Phase I, and II and into Phase III without gathering the attention of analyst, many of whom specialize by industry, seems like a major oddity. An examination of these extremely under covered firms deserves more attention. It may be necessary to extend the timeframe of the sample to gather sufficient data.

While I was correct regarding the directionality of the beta associated with press releases one year prior to approval across all models and windows this metric never yielded significant data. It is possible that press releases are not an effective measure for transparency because they can cover many different corporate events and announcements. A large number of press releases released in a given year means that the firm is extremely communicative but does not necessarily guarantee that the information released is substantive. A firm is required to release an 8-K whenever it communicates material information[10] to the public. The definition of material is vague and as such can mean many different things. A firm may release

[10] Any information about a company that may cause a change in the price of a share of its stock

an 8-K for anything a minor change in company bylaws, to a major change like the hiring or firing of a key executive. Using the sheer number that a company releases may not be a viable measure for transparency. Ideally, if there was a way to quantify the information content of each individual press release on a scale from uninformative to highly informative that would much improve the validity of the measure. I predict this may yield similar results to my findings regarding analyst coverage.

My hypothesis surrounding cumulative abnormal returns surrounding earnings announcements was incorrect. The beta with which it was associated was consistently positive and significant (barring the interaction), the opposite of what I expected. Rather than decreasing cumulative abnormal returns surrounding Phase III approval, firms with larger cumulative abnormal returns surrounding earnings actually saw larger returns. I expected that firms with greater quarterly cumulative abnormal returns had earnings reports that were inherently more informative. The more information in the quarterly earnings report the greater expected cumulative abnormal return surrounding the report should be. More informative reports mean more information about the firm exists and the more effectively the stock should be priced. These assumptions did not hold true. This area deserves more attention.

This research helps illuminate a potential risk factor for which stock pricing methods could be adjusted to increase their accuracy: transparency. While it is difficult to quantify firms that have positive fundamentals but are less transparent have potential for excess returns. This paper affirms that analyst coverage is an appropriate proxy for transparency and as such absolute return managers may benefit from seeking out under covered companies.

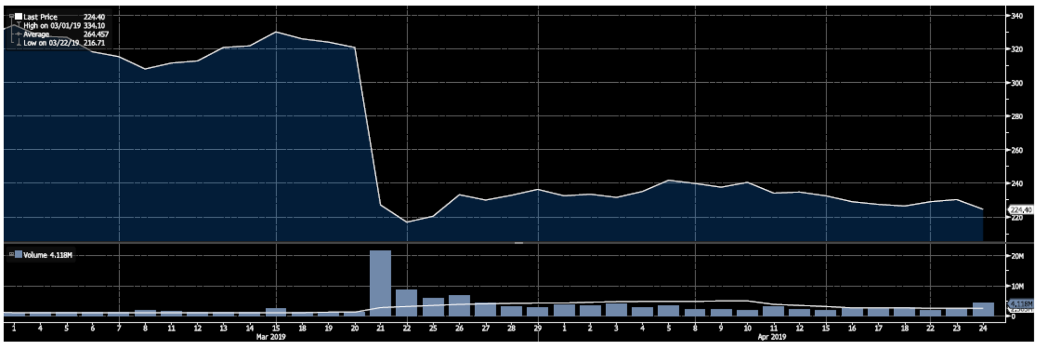
There are also implications from a policy perspective. If efficiency and price discovery is the goal of markets then pharmaceutical and biotechnology company's deserve special attention. Efficiency could through improved by the enforcement of a mechanism to either mandate or encourage increased transparency from these types of firms. Increased transparency would eliminate a good deal of randomness from stock selection and allow institutions and retail investors to more effectively allocate their capital. Uncertainty decreases the amount a person is willing to pay for something regardless of its inherent worth. The market can more effectively price a good the more they understand about the good, whether it be a real good or a financial one. Given the large potential cash inflows and high degree of uncertainty from a Phase III drug approval announcements, all parties benefit from decreasing this information asymmetry. Periodic data releases and potentially mandated incremental reports to company shareholders should increase overall market efficiency. A more informed market is a more efficient market, and this is especially true for the pharmaceutical and biotechnology industry.

Attachment 1: Spark Therapeutics

Bloomberg

BIIB US Equity (Biogen Inc)

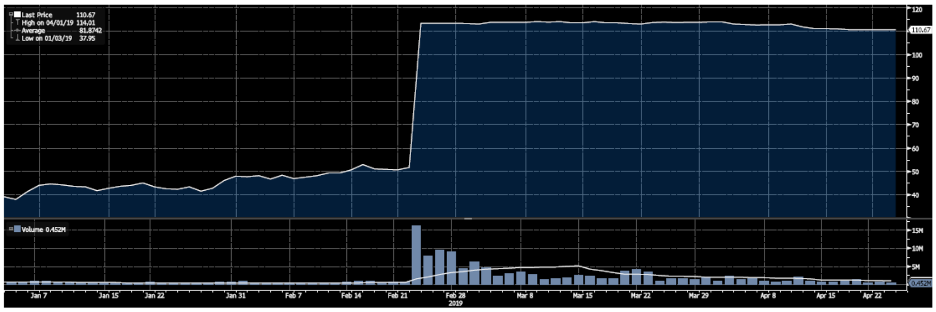
BIIB US Equity (Biogen Inc)



Attachment 2: Biogen

Bloomberg

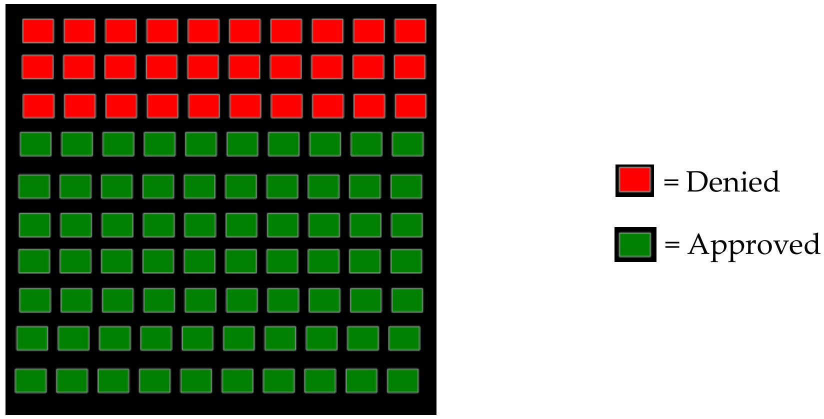
ONCE US Equity (Spark Therapeutics Inc)
ONCE US Equity (Spark Therapeutics Inc)



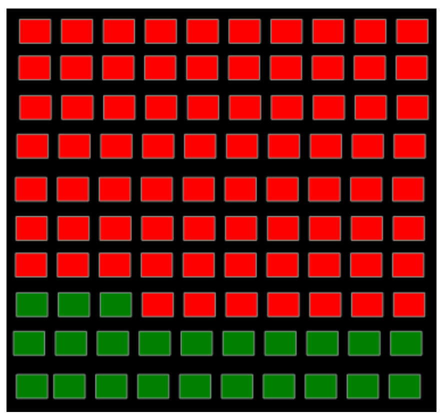
Bloomberg ®Charts 1 - 1

Attachment 3: Visual Representation of Likelihood of Approval

Phase I:



Phase II:



Phase III:

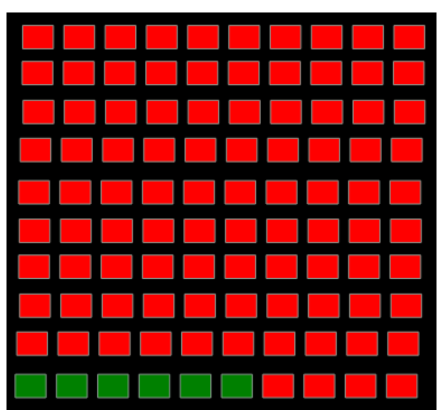


Table 1: Variable Names and Descriptions

Table One: Variable Names and Descriptions	
Variable Name	Description
8Ks	Press Releases (8Ks) 1 year prior to approval
Coverage	# of Analyst Covering company at the announcement +1
Phase 3 Approval Anncmt. Return: MM [-3,+3]	Absolute Value of Market Model Cumulative Abnormal Returns Surrounding Phase 3 approvals [-3,+3]
Phase 3 Approval Anncmt. Return: MM [-1,+1]	Absolute Value of Market Model Cumulative Abnormal Returns Surrounding Phase 3 approvals [-1,+1]
Phase 3 Approval Anncmt. Return: FFPM [-3,+3]	Absolute Value of Fama French Plus Mometum Cumulative Abnormal Returns Surrounding Phase 3 approvals [-3,+3]
Phase 3 Approval Anncmt. Return:FFPM [-1,+1]	Absolute Value of Fama French Plus Mometum Cumulative Abnormal Returns Surrounding Phase 3 approvals [-1,+1]
Ln8ks	Natural Log of Press Releases (8Ks) 1 year prior to approval + 1
LnCoverage	Natural Log of # of Analyst Covering company at the announcement +1
Total Assets	Total Assets
CAPEX	Capital Expenditures
EPS	EPS Diluted Including Extraordinary Items
Net Income	Net Income
Operating Income	Operating Income After Depreciation
R+D	In Process R+D
Sales	Sales
Earnings Anncmt. Return: MM [-1,+1]	Average Absolute Value of Market Model Cumulative Abnormal Returns Surrounding Quarterly Earnings Announcement [-1,+1]
Earnings Anncmt. Return: MM [-3,+3]	Average Absolute Value of Market Model Cumulative Abnormal Returns Surrounding Quarterly Earnings Announcement [-3,+3]
Earnings Anncmt. Return: FFPM [-1,+1]	Average Absolute Value of Fama French Plus Mometum Cumulative Abnormal Returns Surrounding Quarterly Earnings Announcement [-1,+1]
Earnings Anncmt. Return: FFPM [-3,+3]	Average Absolute Value of Fama French Plus Mometum Cumulative Abnormal Returns Surrounding Quarterly Earnings Announcement [-3,+3]

Table 2: Descriptive Statistics

Table 2: Descriptives								
Transparency:	**N**	**Mean**	**Median**	**Standard Deviation**	**25%**	**75%**	**Min**	**Max**
Press Releases (8Ks) 1 year prior to approval	260	16.5769	14	10.5156	10.25	18	2	52
# of Analyst Covering company at the approval +1	260	14.2115	10	10.2172	6	25	0	33
Natural Log of Press Releases (8Ks) 1 year prior to approval + 1	260	1.1887	1.1761	0.2111	1.0508	1.2788	0.4771	1.7243
Natural Log of # of Analyst Covering company at the approval +1	260	1.0636	1.0414	0.3454	0.8451	1.4150	0.0000	1.5315
Returns Surrounding Phase III Approval:	**N**	**Mean**	**Median**	**Standard Deviation**	**25%**	**75%**	**Min**	**Max**
Absolute Value of Market Model Cumulative Abnormal Returns Surrounding Phase 3 approvals [-3,+3]	260	0.0559	0.0390	0.0530	0.0145	0.0786	0.0001	0.1824
Absolute Value of Market Model Cumulative Abnormal Returns Surrounding Phase 3 approvals [-1,+1]	260	0.0379	0.0250	0.0367	0.0097	0.0549	0.0000	0.1298
Absolute Value of Fama French Plus Momentum Cumulative Abnormal Returns Surrounding Phase 3 approvals [-3,+3]	260	0.0574	0.0381	0.0552	0.0136	0.0832	0.0002	0.1822
Absolute Value of Fama French Plus Momentum Cumulative Abnormal Returns Surrounding Phase 3 approvals [-1,+1]	260	0.0377	0.0249	0.0359	0.0091	0.0572	0.0000	0.1225
Returns Surrounding Quarterly Earnings Announcements:	**N**	**Mean**	**Median**	**Standard Deviation**	**25%**	**75%**	**Min**	**Max**
Average Absolute Value of Market Model Cumulative Abnormal Returns Surrounding Quarterly Earnings Announcement [-1,+1]	253	0.0556	0.0490	0.0342	0.0302	0.0735	0.0038	0.1409
Average Absolute Value of Market Model Cumulative Abnormal Returns Surrounding Quarterly Earnings Announcement [-3,+3]	253	0.0748	0.0602	0.0453	0.0405	0.1006	0.0119	0.1822
Average Absolute Value of Fama French Plus Momentum Cumulative Abnormal Returns Surrounding Quarterly Earnings Announcement [-1,+1]	253	0.0548	0.0447	0.0333	0.0282	0.0734	0.0024	0.1340
Average Absolute Value of Fama French Plus Momentum Cumulative Abnormal Returns Surrounding Quarterly Earnings Announcement [-3,+3]	253	0.0745	0.0611	0.0481	0.0366	0.1014	0.0110	0.1909
Financial Control Variables (in millions):	**N**	**Mean**	**Median**	**Standard Deviation**	**25%**	**75%**	**Min**	**Max**
Total Assets	254	$29,336.10	$390.88	$47,771.68	$102.16	$51,536.00	$3.64	$152,807.00
Capital Expenditures	254	$264.91	$3.31	$446.35	$0.17	$398.18	$	$1,533.00
EPS Diluted Including Extraordinary Items	256	-$0.08	-$0.31	$2.16	-$1.07	$1.14	-$8.51	$4.37
Net Income	256	$1,292.68	-$12.98	$2,643.72	-$48.33	$1,416.18	-$5,325.00	$8,719.00
Operaing Income After Depreciation	255	$1,927.95	-$10.12	$3,381.97	-$42.47	$3,133.00	-$445.74	$11,041.00
In Processs R+D	256	$27.73	$	$82.74	$	$	$	$343.00
Sales	256	$7,245.57	$37.15	$11,842.35	$0.80	$12,757.75	$	$38,843.00

Table 3: Correlation Matrix

Spearman Correlation Coefficients Prob > |r| under H0: Rho=0																			
	eightk	**coverage**	**abs_three_mm_car**	**abs_one_mm_car**	**abs_three_ffpm_car**	**abs_one_ffpm_car**	**leightk**	**lcoverage**	**ATQ**	**CAPXY**	**EPSFIY**	**NIY**	**OIADPY**	**RDIPY**	**SALEY**	**Earnings Anncmt. Return: MM [-1,+1]**	**Earnings Anncmt. Return: MM [-3,+3]**	**Earnings Anncmt. Return: FFPM [-1,+1]**	**Earnings Anncmt. Return: FFPM [-3,+3]**
eightk	1	-0.01231	0.00313	-0.00133	0.02241	-0.00106	1	-0.01231	0.08461	0.03228	-0.12479	-0.12537	-0.13495	-0.22107	0.06363	-0.00254	-0.00446	-0.01468	0.0058
		0.8434	0.9599	0.983	0.7191	0.9864	<.0001	0.8434	0.1789	0.6086	0.0461	0.0451	0.0312	0.0004	0.3105	0.968	0.9437	0.8162	0.9269
coverage	-0.01231	1	-0.38974	-0.40156	-0.37631	-0.39229	-0.01231	1	0.81944	0.76478	0.44881	0.33085	0.42035	0.4567	0.74989	-0.43079	-0.50372	-0.4602	-0.50507
	0.8434		<.0001	<.0001	<.0001	<.0001	0.8434	<.0001	<.0001	<.0001	<.0001	<.0001	<.0001	<.0001	<.0001	<.0001	<.0001	<.0001	<.0001
abs_three_mm_car	0.00313	-0.38974	1	0.61073	0.81598	0.56741	0.00313	-0.38974	-0.51769	-0.48517	-0.40019	-0.38575	-0.43473	-0.30346	-0.50257	0.3643	0.4171	0.36348	0.43353
	0.9599	<.0001		<.0001	<.0001	<.0001	0.9599	<.0001	<.0001	<.0001	<.0001	<.0001	<.0001	<.0001	<.0001	<.0001	<.0001	<.0001	<.0001
abs_one_mm_car	-0.00133	-0.40156	0.61073	1	0.56706	0.79619	-0.00133	-0.40156	-0.52042	-0.51124	-0.37632	-0.39109	-0.4366	-0.27216	-0.48262	0.39297	0.39661	0.39775	0.41504
	0.983	<.0001	<.0001		<.0001	<.0001	0.983	<.0001	<.0001	<.0001	<.0001	<.0001	<.0001	<.0001	<.0001	<.0001	<.0001	<.0001	<.0001
abs_three_ffpm_car	0.02241	-0.37631	0.81598	0.56706	1	0.58626	0.02241	-0.37631	-0.50161	-0.47939	-0.42886	-0.43432	-0.49047	-0.28017	-0.50324	0.3773	0.38717	0.36695	0.39457
	0.7191	<.0001	<.0001	<.0001		<.0001	0.7191	<.0001	<.0001	<.0001	<.0001	<.0001	<.0001	<.0001	<.0001	<.0001	<.0001	<.0001	<.0001
abs_one_ffpm_car	-0.00106	-0.39229	0.56741	0.79619	0.58626	1	-0.00106	-0.39229	-0.52674	-0.50897	-0.37104	-0.37464	-0.43664	-0.27366	-0.48905	0.32763	0.35509	0.35433	0.3998
	0.9864	<.0001	<.0001	<.0001	<.0001		0.9864	<.0001	<.0001	<.0001	<.0001	<.0001	<.0001	<.0001	<.0001	<.0001	<.0001	<.0001	<.0001
leightk	1	-0.01231	0.00313	-0.00133	0.02241	-0.00106	1	-0.01231	0.08461	0.03228	-0.12479	-0.12537	-0.13495	-0.22107	0.06363	-0.00254	-0.00446	-0.01468	0.0058
	<.0001	0.8434	0.9599	0.983	0.7191	0.9864		0.8434	0.1789	0.6086	0.0461	0.0451	0.0312	0.0004	0.3105	0.968	0.9437	0.8162	0.9269
lcoverage	-0.01231	1	-0.38974	-0.40156	-0.37631	-0.39229	-0.01231	1	0.81944	0.76478	0.44881	0.33085	0.42035	0.4567	0.74989	-0.43079	-0.50372	-0.4602	-0.50507
	0.8434	<.0001	<.0001	<.0001	<.0001	<.0001	0.8434		<.0001	<.0001	<.0001	<.0001	<.0001	<.0001	<.0001	<.0001	<.0001	<.0001	<.0001
ATQ	0.08461	0.81944	-0.51769	-0.52042	-0.50161	-0.52674	0.08461	0.81944	1	0.92699	0.5736	0.49571	0.56468	0.42023	0.91393	-0.54001	-0.6372	-0.57328	-0.64676
	0.1789	<.0001	<.0001	<.0001	<.0001	<.0001	0.1789	<.0001		<.0001	<.0001	<.0001	<.0001	<.0001	<.0001	<.0001	<.0001	<.0001	<.0001
CAPXY	0.03228	0.76478	-0.48517	-0.51124	-0.47939	-0.50897	0.03228	0.76478	0.92699	1	0.58628	0.49948	0.57998	0.42605	0.90807	-0.51219	-0.6281	-0.54639	-0.62993
	0.6086	<.0001	<.0001	<.0001	<.0001	<.0001	0.6086	<.0001	<.0001		<.0001	<.0001	<.0001	<.0001	<.0001	<.0001	<.0001	<.0001	<.0001
EPSFIY	-0.12479	0.44881	-0.40019	-0.37632	-0.42886	-0.37104	-0.12479	0.44881	0.5736	0.58628	1	0.88714	0.84867	0.2996	0.67172	-0.49542	-0.51946	-0.50468	-0.50658
	0.0461	<.0001	<.0001	<.0001	<.0001	<.0001	0.0461	<.0001	<.0001	<.0001		<.0001	<.0001	<.0001	<.0001	<.0001	<.0001	<.0001	<.0001
NIY	-0.12537	0.33085	-0.38575	-0.39109	-0.43432	-0.37464	-0.12537	0.33085	0.49571	0.49948	0.88714	1	0.9091	0.2049	0.56557	-0.53749	-0.50632	-0.50517	-0.47271
	0.0451	<.0001	<.0001	<.0001	<.0001	<.0001	0.0451	<.0001	<.0001	<.0001	<.0001		<.0001	0.001	<.0001	<.0001	<.0001	<.0001	<.0001
OIADPY	-0.13495	0.42035	-0.43473	-0.4366	-0.49047	-0.43664	-0.13495	0.42035	0.56468	0.57998	0.84867	0.9091	1	0.36361	0.64609	-0.55066	-0.52816	-0.51227	-0.49278
	0.0312	<.0001	<.0001	<.0001	<.0001	<.0001	0.0312	<.0001	<.0001	<.0001	<.0001	<.0001		<.0001	<.0001	<.0001	<.0001	<.0001	<.0001
RDIPY	-0.22107	0.4567	-0.30346	-0.27216	-0.28017	-0.27366	-0.22107	0.4567	0.42023	0.42605	0.2996	0.2049	0.36361	1	0.44566	-0.27738	-0.35163	-0.28684	-0.35212
	0.0004	<.0001	<.0001	<.0001	<.0001	<.0001	0.0004	<.0001	<.0001	<.0001	<.0001	0.001	<.0001		<.0001	<.0001	<.0001	<.0001	<.0001
SALEY	0.06363	0.74989	-0.50257	-0.48262	-0.50324	-0.48905	0.06363	0.74989	0.91393	0.90807	0.67172	0.56557	0.64609	0.44566	1	-0.5156	-0.64784	-0.55089	-0.65671
	0.3105	<.0001	<.0001	<.0001	<.0001	<.0001	0.3105	<.0001	<.0001	<.0001	<.0001	<.0001	<.0001	<.0001		<.0001	<.0001	<.0001	<.0001
Earnings Anncmt. Return: MM [-1,+1]	-0.00254	-0.43079	0.3643	0.39297	0.3773	0.32763	-0.00254	-0.43079	-0.54001	-0.51219	-0.49542	-0.53749	-0.55066	-0.27738	-0.5156	1	0.77651	0.94756	0.74031
	0.968	<.0001	<.0001	<.0001	<.0001	<.0001	0.968	<.0001	<.0001	<.0001	<.0001	<.0001	<.0001	<.0001	<.0001		<.0001	<.0001	<.0001
Earnings Anncmt. Return: MM [-3,+3]	-0.00446	-0.50372	0.4171	0.39661	0.38717	0.35509	-0.00446	-0.50372	-0.6372	-0.6281	-0.51946	-0.50632	-0.52816	-0.35163	-0.64784	0.77651	1	0.77057	0.94374
	0.9437	<.0001	<.0001	<.0001	<.0001	<.0001	0.9437	<.0001	<.0001	<.0001	<.0001	<.0001	<.0001	<.0001	<.0001	<.0001		<.0001	<.0001
Earnings Anncmt. Return: FFPM [-1,+1	-0.01468	-0.4602	0.36348	0.39775	0.36695	0.35433	-0.01468	-0.4602	-0.57328	-0.54639	-0.50468	-0.50517	-0.51227	-0.28684	-0.55089	0.94756	0.77057	1	0.78019
	0.8162	<.0001	<.0001	<.0001	<.0001	<.0001	0.8162	<.0001	<.0001	<.0001	<.0001	<.0001	<.0001	<.0001	<.0001	<.0001	<.0001		<.0001
Earnings Anncmt. Return: FFPM [-3,+3]	0.0058	-0.50507	0.43353	0.41504	0.39457	0.3998	0.0058	-0.50507	-0.64676	-0.62993	-0.50658	-0.47271	-0.49278	-0.35212	-0.65671	0.74031	0.94374	0.78019	1
	0.9269	<.0001	<.0001	<.0001	<.0001	<.0001	0.9269	<.0001	<.0001	<.0001	<.0001	<.0001	<.0001	<.0001	<.0001	<.0001	<.0001	<.0001	

Table 4: Cumulative Abnormal Returns Market Model -1, +1 Window

	Dependent variable:				
	-1/+1 Market Model				
	(1)	(2)	(3)	(4)	(5)
Natural Log Coverage	-0.035***		-0.034***		-0.033***
	(0.006)		(0.006)		(0.007)
Natural Log Press Releases		-0.012	-0.010		-0.010
		(0.011)	(0.010)		(0.010)
Earnings				0.280***	0.165**
				(0.066)	(0.068)
Constant	0.075***	0.052***	0.086***	0.023***	0.076***
	(0.007)	(0.013)	(0.014)	(0.004)	(0.015)
Observations	260	260	260	253	253
R^2	0.105	0.005	0.109	0.067	0.149
Adjusted R^2	0.102	0.001	0.102	0.063	0.139
Residual Std. Error	0.035 (df = 258)	0.037 (df = 258)	0.035 (df = 257)	0.036 (df = 251)	0.034 (df = 249)
F Statistic	30.382*** (df = 1; 258)	1.245 (df = 1; 258)	15.665*** (df = 2; 257)	18.021*** (df = 1; 251)	14.508*** (df = 3; 249)
Note:					*p<0.1; **p<0.05; ***p<0.01

Table 5: Cumulative Abnormal Returns Market Model -3, +3 Window

	Dependent variable:				
	-3/+3 Market Model				
	(6)	(7)	(8)	(9)	(10)
Natural Log Coverage	-0.056***		-0.055***		-0.050***
	(0.009)		(0.009)		(0.010)
Natural Log Press Releases		-0.017	-0.014		-0.013
		(0.016)	(0.015)		(0.014)
Earnings				0.379***	0.209***
				(0.070)	(0.076)
Constant	0.115***	0.077***	0.132***	0.028***	0.109***
	(0.010)	(0.019)	(0.020)	(0.006)	(0.023)
Observations	260	260	260	253	253
R^2	0.132	0.005	0.135	0.104	0.185
Adjusted R^2	0.129	0.001	0.129	0.100	0.175
Residual Std. Error	0.049 (df = 258)	0.053 (df = 258)	0.049 (df = 257)	0.051 (df = 251)	0.048 (df = 249)
F Statistic	39.348*** (df = 1; 258)	1.240 (df = 1; 258)	20.134*** (df = 2; 257)	28.985*** (df = 1; 251)	18.809*** (df = 3; 249)
Note:					*p<0.1; **p<0.05; ***p<0.01

Table 6: Cumulative Abnormal Returns Fama French Plus Momentum Model -1, +1 Window

	Dependent variable:				
	-1/+1 Fama French Plus Momentum				
	(11)	(12)	(13)	(14)	(15)
Natural Log Coverage	-0.036***		-0.036***		-0.035***
	(0.006)		(0.006)		(0.007)
Natural Log Press Releases		-0.012	-0.010		-0.010
		(0.011)	(0.010)		(0.010)
Earnings				0.283***	0.142**
				(0.066)	(0.069)
Constant	0.076***	0.052***	0.088***	0.023***	0.079***
	(0.007)	(0.013)	(0.013)	(0.004)	(0.015)
Observations	260	260	260	253	253
R^2	0.123	0.005	0.126	0.068	0.160
Adjusted R^2	0.119	0.001	0.119	0.064	0.150
Residual Std. Error	0.034 (df = 258)	0.036 (df = 258)	0.034 (df = 257)	0.035 (df = 251)	0.033 (df = 249)
F Statistic	36.030*** (df = 1; 258)	1.278 (df = 1; 258)	18.499*** (df = 2; 257)	18.251*** (df = 1; 251)	15.776*** (df = 3; 249)
Note:					*p<0.1; **p<0.05; ***p<0.01

Table 7: Cumulative Abnormal Returns Fama French Plus Momentum Model -3, +3 Window

	Dependent variable:				
	-3/+3 Fama French Plus Momentum				
	(16)	(17)	(18)	(19)	(20)
Natural Log Coverage	-0.054 ***		-0.054 ***		-0.046 ***
	(0.009)		(0.009)		(0.011)
Natural Log Press Releases		-0.021	-0.018		-0.017
		(0.016)	(0.015)		(0.015)
Earnings				0.365 ***	0.212 ***
				(0.069)	(0.076)
Constant	0.115 ***	0.082 ***	0.136 ***	0.031 ***	0.112 ***
	(0.010)	(0.020)	(0.021)	(0.006)	(0.024)
Observations	260	260	260	253	253
R^2	0.115	0.006	0.119	0.099	0.166
Adjusted R^2	0.111	0.003	0.113	0.096	0.156
Residual Std. Error	0.052 (df = 258)	0.055 (df = 258)	0.052 (df = 257)	0.053 (df = 251)	0.051 (df = 249)
F Statistic	33.482 *** (df = 1; 258)	1.671 (df = 1; 258)	17.436 *** (df = 2; 257)	27.629 *** (df = 1; 251)	16.530 *** (df = 3; 249)
Note:					*p <0.1; **p <0.05; ***p <0.01

Table 8: Above and Below Median Transparency

Table 8 Breakdown Above and Below Median				
Press Releases (8Ks) 1 year prior to approval	**Below Median**	**Above Median**	**Difference**	**P Value**
Phase 3 Approval Anncmt. Return: MM [-1,+1]	0.03698	0.03879	0.00180	0.69290
Phase 3 Approval Anncmt. Return:FFPM [-1,+1]	0.03650	0.03881	0.00232	0.60397
# of Analyst Covering company at the annoucement	**Below Median**	**Above Median**	**Difference**	**P Value**
Phase 3 Approval Anncmt. Return: MM [-1,+1]	0.04892	0.02685	-0.02207	7.60094E-07
Phase 3 Approval Anncmt. Return:FFPM [-1,+1]	0.04841	0.02690	-0.02151	8.27861E-07
Earnings Anncmt. Return: MM [-1,+1]	**Below Median**	**Above Median**	**Difference**	**P Value**
Phase 3 Approval Anncmt. Return: MM [-1,+1]	0.02824	0.04753	0.01930	1.71553E-05
Earnings Anncmt. Return: FFPM [-1,+1]	**Below Median**	**Above Median**	**Difference**	**P Value**
Phase 3 Approval Anncmt. Return:FFPM [-1,+1]	0.02869	0.04662	0.01793	4.54536E-05

Table 9: Most Versus Least Transparent Firms

Most Vs. Least Transparent				
Model	High Transparency	Low Transparency	Difference	P-Value
Phase 3 Approval Anncmt. Return: MM [-1,+1]	0.04868	0.08418	-0.03550	0.03869
Phase 3 Approval Anncmt. Return:FFPM [-1,+1]	0.04759	0.07778	-0.03019	0.04306

Table 10: Cumulative Abnormal Returns Fama French Plus Momentum Model -1, +1 Window with Dummy Variable for Least Transparent:

	Dependent variable:
	-1/+1 Fama French Plus Momentum (21)
Natural Log Coverage	-0.003
	(0.010)
Natural Log Press Releases	-0.029***
	(0.007)
Earnings	0.179**
	(0.070)
Least Transparent	0.022**
	(0.011)
Constant	0.063***
	(0.017)
Observations	252
R^2	0.171
Adjusted R^2	0.158
Residual Std. Error	0.033 (df = 247)
F Statistic	12.745*** (df = 4; 247)
Note:	*p<0.1; **p<0.05; ***p<0.01

Table 11: Fama French Plus Momentum Model Nonlinear Coverage

	Dependent variable:	
	-1/+1 Fama French Plus Momentum	
	(22)	(23)
Natural Log Coverage	-0.036***	0.057**
	(0.006)	(0.029)
Natural Log Coverage Squared		-0.047***
		(0.014)
Constant	0.076***	0.036***
	(0.007)	(0.014)
Observations	260	260
R2	0.123	0.158
Adjusted R2	0.119	0.152
Residual Std. Error	0.034 (df = 258)	0.033 (df = 257)
F Statistic	36.030*** (df = 1; 258)	24.177*** (df = 2; 257)
Note:		*p<0.1; **p<0.05; ***p<0.01

Chart One: Distribution of Analyst Coverage (1 Year Prior to Phase III Approval)

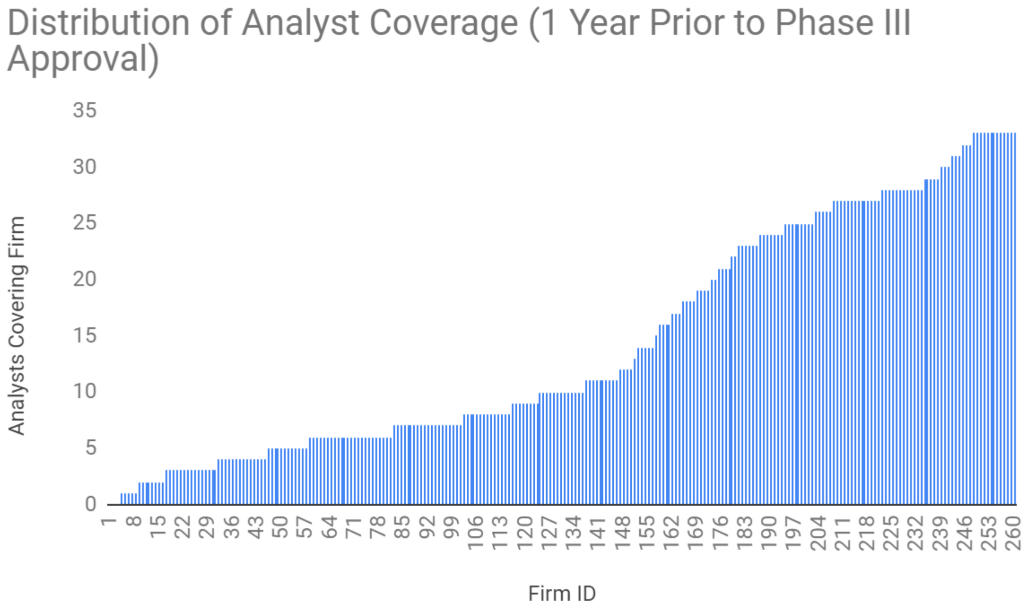


Table 12: Fama French Plus Momentum Model Coverage and Earnings Interaction

	Dependent variable:	
	-1/+1 Fama French Plus Momentum	
	(24)	(25)
Natural Log Coverage	-0.035***	-0.043***
	(0.007)	(0.012)
Earnings	0.145**	-0.016
	(0.069)	(0.222)
Interaction		0.155
		(0.202)
Constant	0.067***	0.076***
	(0.010)	(0.015)
Observations	253	253
R^2	0.156	0.158
Adjusted R^2	0.150	0.148
Residual Std. Error	0.033 (df = 250)	0.033 (df = 249)
F Statistic	23.150*** (df = 2; 250)	15.602*** (df = 3; 249)
Note:		*p<0.1; **p<0.05; ***p<0.01

Works Cited

Brown, Stephen J., and Jerold B. Warner. "Using Daily Stock Returns." Journal of Financial Economics, vol. 14, no. 1, 1985, pp. 3–31., doi:10.1016/0304-405x(85)90042.

Bloomberg L.P. Stock Price graph for Biogen. 12/1/19 to 04/24/19. Bloomberg terminal, 24 April 2019.

Bloomberg L.P. Stock Price graph for Spark Therapeutics. 12/1/19 to 04/24/19. Bloomberg terminal, 24 April 2019.

Chang, Xin, et al. "Analyst Coverage and Financing Decisions." *The Journal of Finance*, vol. 61, no. 6, Dec. 2006, doi:10.2139/ssrn.571065.

Compustat Industrial [Annual Data]. 2009 to 2018. Available: Standard & Poor's/Compustat 04/24/19. Retrieved from Wharton Research Data Service.

CRSP Stocks. 2009 to 2018. Available: Center For Research in Security Prices. Graduate School of Business. University of Chicago 04/24/19. Retrieved from Wharton Research Data Service.

Dewenter, Kathryn L., and Vincent A. Warther. "Dividends, Asymmetric Information, and Agency Conflicts: Evidence from a Comparison of the Dividend Policies of Japanese and U.S. Firms." The Journal of Finance, vol. 53, no. 3, 1998, pp. 879–904., doi:10.1111/0022-1082.00038.

Dimasi, Joseph A., et al. "Innovation in the Pharmaceutical Industry: New Estimates of R&D Costs." *Journal of Health Economics*, vol. 47, 2016, pp. 20–33., doi:10.1016/j.jhealeco.2016.01.012.

Fama, Eugene F. "Efficient Capital Markets: A Review of Theory and Empirical Work." *The Journal of Finance*, vol. 25, no. 2, 1970, p. 383., doi:10.2307/2325486.

Fama, Eugene F., and Kenneth R. French. "Common Risk Factors in the Returns on Stocks and Bonds." Journal of Financial Economics, vol. 33, no. 1, 1993, pp. 3–56., doi:10.1016/0304-405x(93)90023-5.

Hargrave, Marshall. "How to Use the Winsorized Mean." *Investopedia*, Investopedia, 17 Apr. 2019, www.investopedia.com/terms/w/winsorized_mean.asp.

Hwang, Thomas J. "Stock Market Returns and Clinical Trial Results of Investigational Compounds: An Event Study Analysis of Large Biopharmaceutical Companies." PLoS ONE, vol. 8, no. 8, July 2013, doi:10.1371/journal.pone.0071966.

Keefe, Patrick Radden. "Inside the Biggest-Ever Hedge-Fund Scandal." *The New Yorker*, The New Yorker, 19 June 2017, www.newyorker.com/magazine/2014/10/13/empire-edge.

Landsman, Wayne R., and Edward L. Maydew. "Beaver (1968) Revisited: Has the Information Content of Annual Earnings Announcements Declined in the Past Three Decades?" SSRN Electronic Journal, 2000, doi:10.2139/ssrn.204068.

Office of the Commissioner. "The Drug Development Process - Step 3: Clinical Research." *U S Food and Drug Administration Home Page*, Office of the Commissioner, www.fda.gov/forpatients/approvals/drugs/ucm405622.htm.

Opong, Kwaku K. "The Information Content Of Interim Financial Reports: Uk Evidence." Journal of Business Finance & Accounting, vol. 22, no. 2, 1995, pp. 269–279., doi:10.1111/j.1468-5957.1995.tb00683.x.

Picardo, Elvis. “Phase 3.” Investopedia, Investopedia, 1 June 2018, www.investopedia.com/terms/p/phase-3.asp.

Rothenstein, Jeffrey M., et al. “Company Stock Prices Before and After Public Announcements Related to Oncology Drugs.” JNCI: Journal of the National Cancer Institute, vol. 103, no. 20, 2011, pp. 1507–1512., doi:10.1093/jnci/djr338.

Sarkar, Salil K., and Pieter J. De Jong. “Market Response to FDA Announcements.” The Quarterly Review of Economics and Finance, vol. 46, no. 4, 2006, pp. 586–597., doi:10.1016/j.qref.2005.01.003.

Sharma, Anurag, and Nelson Lacey. “Linking Product Development Outcomes to Market Valuation of the Firm: The Case of the U.S. Pharmaceutical Industry*.” Journal of Product Innovation Management, vol. 21, no. 5, 2004, pp. 297–308., doi:10.1111/j.0737-6782.2004.00084.x.

Sharpe, William F. “Capital Asset Prices: A Theory of Market Equilibrium under Conditions of Risk.” The Journal of Finance, vol. 19, no. 3, 1964, p. 425., doi:10.2307/2977928.

Small Cap Analyst Coverage: An ‘Under-the-Radar’ Dilemma” World Federation of Exchanges, 2010.

Syed, Ali Murad, and Ishtiaq Ahmad Bajwa. “Earnings Announcements, Stock Price Reaction and Market Efficiency – the Case of Saudi Arabia.” International Journal of Islamic and Middle Eastern Finance and Management, vol. 11, no. 3, 2018, pp. 416–431., doi:10.1108/imefm-02-2017-0044.

Wharton Research Data Services. , 1993. Internet resource.

Wilcox, Stephen E. “Investor Psychology and Security Market Under- and Overreactions.” CFA Digest, vol. 29, no. 2, 1999, pp. 69–71., doi:10.2469/dig.v29.n2.480.