5-2016

Event-Based Biotechnology Stock Price Movement: Valuing Success and Failure in Biotechnology Product Development

Faris Sumadi
University of Massachusetts Boston

Event-Based Biotechnology Stock Price Movement:

Valuing Success and Failure in Biotechnology Product Development

Honors Thesis Paper

Faris Sumadi
University of Massachusetts Boston
College of Business Management Honors Program

May 17, 2016

Introduction:

Biotechnology investment, in the second quarter of 2015, hauled in a record $2.3 billion worth of venture capital. The 126 deals struck marked the biggest quarterly investment (up 32% from the prior quarter) since reporting started in 1995. With $3.8 billion invested in these pre-IPO ventures by mid-2015, the biotech industry soared past the $6 billion of venture capital cash invested in 2014.

These numbers illustrate how early-stage research, with unproven science, has been revived after a decade of VCs shying away. Out of the $2.3 billion raised in Q2, $1.5 billion went to early-stage companies while $733 million went to startups receiving money for the first time. To make this paradigm shift more evident, venture capital money has not been flocking to a specific disease category (for instance, only within the cancer immunotherapy space). In fact, Denali Therapeutics, a company researching neurodegenerative diseases, raised $217 million of that $2.3 billion alone. Others in the top ten included three gene therapy companies, an antibiotics developer (Melinta Therapeutics) raising $67 million, and CytomX advancing its "probody therapeutics" or antibodies engineered to target tumors while leaving healthy tissues alone (raised $70 million).

It is important to understand why there has been a pre-IPO investment frenzy the past several years: there is a clear and attractive exit strategy with post-IPO valuation potential. To give a general example, Aduro Biotech staged a $119 million IPO in April, after its $200 million deal with Novartis to develop immunotherapy treatments for cancer, and quickly flew past $1 billion in market value. New public biotech stocks have been pricing above expected IPO ranges yet still have seen significant valuation appreciation.

During the second quarter of 2015, 14 biotech ventures went public and collectively raised around $1.2 billion with the hopes of also delivering tremendous upside to their initial VCs. In fact, the S&P biotech index has risen upwards of 50% (by mid-2015) from the prior year; biotech investors have grossly outperformed investors focusing on any other sector. To mention a specific company, Exelixis popped 50% after releasing positive results in its Phase III drug trial in patients with kidney cancer. With more notable successes within the industry, a significant M&A uptick, a willingness from the Food and Drug Administration to fast-track approval of drugs showing positive results, and heightened collaboration between academia and industry, the biotech sector has been blossoming.

Phase III clinical trial results are very important for biotech companies as they offer insight into the real effectiveness of a drug in human patients and drives the ultimate market valuation. Phase III trials, in the scope of a drug's development process, are the end game with thousands of volunteers with specific diseases participating in a multi-year study to determine if their treatment is statistically significant in combating their condition and produces no intensive adverse reactions (Weintraub 1-3). Upon Phase III approval, a company can sell and market its drug to the masses.

Erik Gordon states, "Biotech is driven by stories, but those stories don't always have happy endings, as the current valuations might imply they do. The logic of the science combined with the hope of the people adds up to huge optimism. We will continue to see the fruits of [genomics] in terms of coming up with therapeutics that work. But every bit of progress just reveals the next difficult hurdle" (Weintraub 3). Producing Phase III results could be the most difficult hurdle that provides a catalyst for future marketability of a new drug treatment.

With this fury of new investment, investors want to know the typical stock price swing associated with the Food and Drug Administration's (FDA) Phase III clinical trial results. The purpose of this research is to determine specific firm characteristics influencing the upside or downside potential upon drug results of biotechnology stocks; the specific firm characteristics involve market capitalization, R&D expenditure value-to-market value, and the type of results "FDA press release" (i.e. success or failure of clinical trial). Daily stock price percentage movements during three separate time frames (for 1 year prior to the Phase III announcement event window, for 3 months prior, and a 6-month period following the FDA's announcement) are also collected for more analysis.

This study hopes to prove three overarching hypotheses. The first hypothesis is that biotechnology stock price upside or downsize surrounding Phase III clinical trial results are inversely proportional to their market capitalization size. The second hypothesis is that biotechnology stock price upside or downsize surrounding Phase III clinical trial results are directly proportional to their R&D expenditure value-to-market value. The third hypothesis is that biotechnology stock price upside or downsize surrounding Phase III clinical trial results are directly proportional their press release news type (success or failure). When analyzing stock returns before the Phase III announcement and following the announcement's immediate stock price reaction, further relationships like pre-announcement insider trading or the absence of arbitrageurs seen by post-negative-announcement stock drift will be investigated as well.

This research hopes to offer investors a risk analysis for investing in biotechnology stocks and give CEOs insight into where their share price may end up based on FDA outcomes. CEOs may attempt, by using this research, to adopt new business strategies to reduce stock price volatility.

Literary Review:

Rothenstein et al. (2011), in an effort to seek indirect evidence of insider trading, hypothesize that oncology (cancer) stock prices increase before public announcements of positive Phase III clinical trials and decrease before negative trial announcements. They investigate 23 positive and 36 negative announcements and their respective company's stock price movement before and after. They find that companies with positive and negative trials diverge after day -60 relative to announcement; they show this by calculating a 9.4% positive change in average price (from baseline) between days -120 to -61 (period 1) and days -60 to -1 (period 2) relative to announcement for stocks that later had positive results versus a -4.5% change (between periods 1 and 2) for stocks with negative announcements. With a two-sided statistical test for the 120 days prior to announcement, they also calculate a mean stock price increasing 13.7% (95% confidence interval = -2.2% to 29.6%) for companies with positive reports and a mean stock price decreasing 0.7% (95% confidence interval = 213.8% to 12.3%) for companies with negative reports (P = .09). The below figure visualizes their statistically significant findings in which they prove their hypothesis:

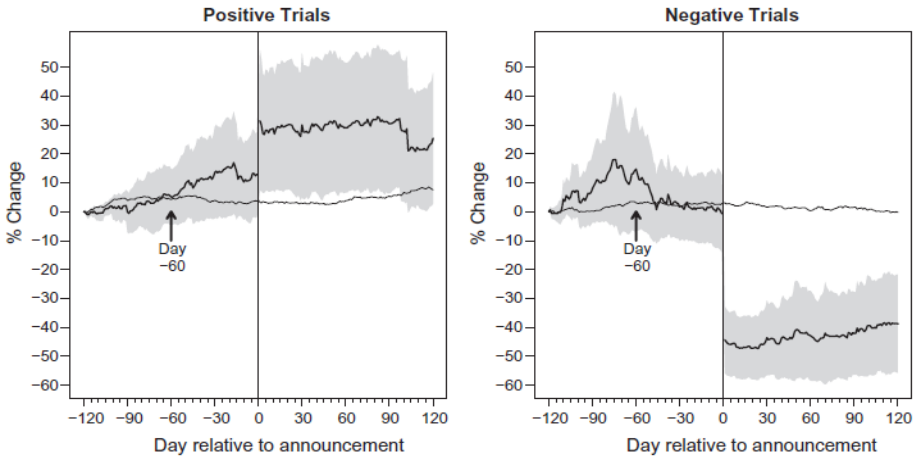


Figure 1. Mean percent change from baseline in company stock prices before and after announcements of positive (n = 23) and negative (n = 36) phase III clinical trials (**black line**). The **shaded area** indicates pointwise 95% confidence intervals for this mean. The **gray line** is the mean standardized value of the National Association of Security Dealers Automated Quotations (NASDAQ) index on corresponding trading days.

(Rothenstein et. al, *Company Stock Prices Before and After Public Announcements Related to Oncology Drugs*, 2011)

In their discussion, they indicate two factors that made the study difficult: many of the companies were large with multidrug portfolios, making their market value less sensitive to the prospects of a single product, and hedge fund influence on stock prices within the time period of 2000 and 2009. They conclude by stating the small-sampled study did not account for the many other factors that may influence a company's stock price. I intend to find the influence of the various factors and limitations discussed in this oncology study and revisit insider trading.

Chan (2003) investigates stock price movement after news and compares them to stocks with similar returns with no identifiable news. He finds that there is strong post-announcement drift for months after bad news (unlike with good news) as investors react slowly to the information [when looking at the above figure from Rothenstein et al. (2011), there is no visualization of a post-announcement drift – which is most likely due to the fact that larger companies dominate that data pool]. He also finds reversals after extreme price movements unaccompanied by public news, even after controlling for firm size and book-to-market; for Chan, this proves consistent with investor overreaction to spurious price movements. Chan furthermore references behavior theories like investors discounting public signals found in Daniel et al. (1998) and investors reacting to prices as opposed to information in Hong and Stein (1999) as some of the many ways in explaining reversal and drift. Chan also references Lee and Swaminathan (2000) that show how momentum is linked to reversal, conditional on trading volume and Hong et al. (2000) that find that more momentum in stocks with no analyst coverage. Chan states that drift and reversal effects are diminished to some degree when small, more illiquid stocks (stocks below $5/share) are eliminated from the data pool; he explains that slow investor reaction and transaction cost preventing arbitrageurs from eliminating the lag (as seen with the higher cost of shorting stocks) are possible explanations to this. Although Chan

discusses results after size and book-to-market related adjustments when describing frictions that slow the diffusion of information to investors. I intend to quantify firm factor significance on biotech-only stocks and investigate post-announcement drift.

Malkiel (2003) references the Fama and French (1993) model which depicts the size-effect of companies on stock price returns. With decades of data, an evident trend emerged: average returns for portfolios formed on the basis of size declined with larger companies; rationale for this, according to Malkiel, may include the preference of liquidity by portfolio managers or that the small-firm effect may have been affected by survivorship betas. When analyzing the Fama-French model, Malkiel reiterates that stocks with low book value-to-market value ratios (value companies) tend to provide higher rates of return than stocks with high book value-to-market value ratios (growth companies), contrary to popular belief. Below is the Fama-French three-factor model, including market beta from the Capital Asset Pricing Model (CAPM). This model will be used to find the predicted stock price return absent of Phase III clinical trial results during the event window:

$$r = R_f + \beta_3(K_m - R_f) + b_s \cdot SMB + b_v \cdot HML + \alpha$$

Bastin and Hubner (2006) find that they could cluster biotechnology stocks according to their responsiveness to political and scientific events following the Bill Clinton and Tony Blair announcement of free availability of raw data contained in the human genome; their clusters include Genomics, Diagnostics/Imaging, Technology-based, and Therapeutics. Through this, they provide rationale for tweaking Fama and French's three-factor model into a 4-factor model in depicting the "normal" return on biotechnology stocks. The fourth factor is an industry-specific patent-based factor that has variable market value of its own following political and

scientific announcements. They argue that patents represent an intangible R&D variable. In constructing the patent-based factor (the average patent market value of a firm) they define it as (MV = Market Value):

$$PMV_t = \frac{MV_t - \left(Cash + Short\ Term\ Investments\right)_t}{Number\ of\ \ Patents\ \ Issued_t}$$

Putting the new factor together with the Fama-French (1993) model, the following four-factor model is obtained under Bastin and Hubner (2006):

$$r_{i,t} = \alpha_i + \beta_{i1} r_{m,t} + \beta_{i2} SMB_t + \beta_{i3} HML_t + \beta_{i4} HPmLP_t + \varepsilon_{i,t} \qquad \forall t \in EP$$

where *ri,t* is the observed (continuously compounded) return of portfolio *i* in excess of the risk-free rate at time *t*; *rm,t* represents excess market return; the size factor *SMB* (small minus big) is the difference between average daily returns of small stock portfolios and big stock portfolios; the book-to-market factor *HML* (high minus low) is the difference between average daily returns of high *BE/ME* stock portfolios and low *BE/ME* stock portfolios, and the industry factor *HPmLP* is the difference between average daily returns of the high-PMV portfolio and the low-PMV portfolio.

When doing their event-study, Bastin and Hubner realize the presence of the HML factor does not enhance the overall significance of the regression (insignificant coefficients for portfolios). Their HP*m*LP measure, as hypothesized, is inversely related to their R&D (PMV) measure.

Ironically, in another study on the market valuation of biotechnology R&D, Hand (2001) classifies the aforementioned patents as a “soft” variable alongside intellectual human capital,

strategic alliances, and joint ventures. He states that contrary to the common view that soft variables are primary drivers of biotechnology valuation, simple balance sheet, income statement, and cash flow data explains 70% of the variance in biotech firms' equity market values within a log-linear regression framework. Hand finds that the elasticity of biotech firms' equity market values with respect to R&D is significantly larger the earlier is the R&D expenditure in the value chain and the greater the growth rate is in R&D spending during the time period of 1989 to 2000; he also finds that biotechnology core income is entirely unrelated to equity market values. Hand states that, under U.S. GAAP, R&D expenditures are not allowed to be capitalized and amortized into income over time and have to be expensed immediately (as they believe there is no significant evidence R&D expenditures are a capital asset with a future alternative use). This means, according to Hand, aggregate balance sheet and income statement variables such as shareholder equity and net income are biased measures of the economic position and earnings of a biotechnology company. Including all R&D expenses, as opposed to singling out patents as the R&D measure, is more representative of biotechnology firm's intensive R&D scope in conclusion. Hand infers that although the huge uncertainty inherent in the production and investment functions of biotechnology companies with regard to R&D exists, investors still value firms based on popular accounting viewpoints.

Titi (2014) examines how stock returns, price, and volatility are affected by R&D expenditures for biotech firms between 2002 and 2013. She confirms at least one of her hypotheses: higher R&D expenditure to market value is related with significant positive stock returns, especially with firms having more than $100 million in spending. Titi also agrees, alongside Hand, that R&D capital absorbs the book-to-market effect; this is likely the reason Bastin and Hubner (2006) end up eliminating it from their tweaked 4-factor model (Titi also

eliminates it as a factor in her regression). Titi states that according to Chan et al. (2001) stocks with high R&D to market ratio tend to be stocks with poor past returns and the market discounts heavily the likelihood of their future recovery by underreacting to manager's signals; this is evidently similar in the earlier analysis of why value stocks tend to outperform growth stocks according to the Fama-French model. Titi also agrees to Xu (2006) when trying to figure out why she rejected her hypothesis that R&D expenditures and volatility are positively linked: "Firms that have more diversified drug portfolios are associated with lower share price volatilities."

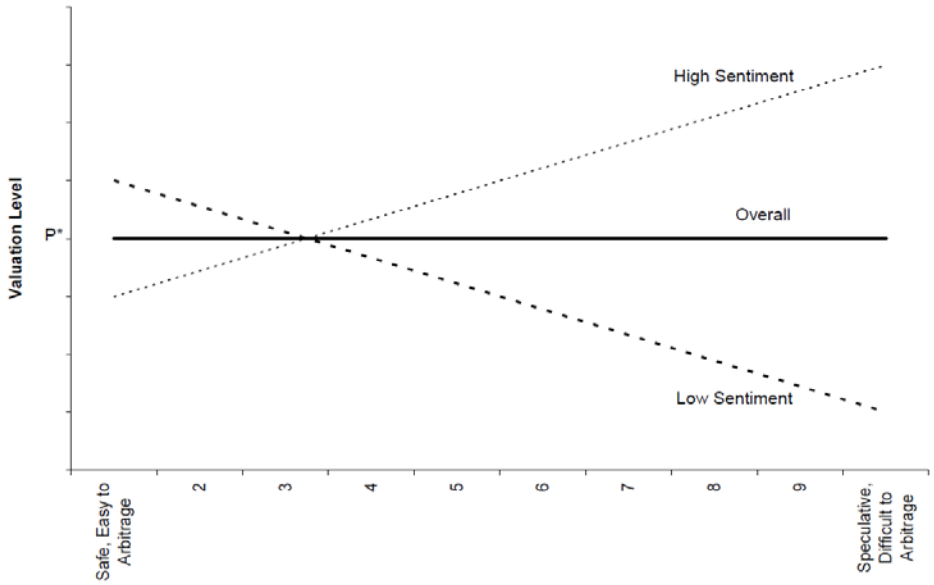
As for soft variables [some alluded to above with Chan et al. (2001)], although Hand (2001) doesn't believe they reflect much in the scope of stock returns when compared to R&D expenditure, he still acknowledges that the extent of collaborations by biotech firm's scientists with star U.S. bio-scientists and the presence of venture capital are powerful predictors of a firm's ultimate success. An additional "soft" variable for biotech stock price movement surrounding Phase III announcements can be related to a bubbling market in light of the sector's recent technological revolution. Pastor and Veronesi (2005) mention that "bubbles" form during technological revolutions and that these revolutions are pronounced by high uncertainty for innovative firms and fast adoption. They state that the nature of this uncertainty changes from idiosyncratic to systematic; as the adoption probability increases, the resulting increase in systematic risk pushes up the discount rates and thus depresses stock prices ultimately countervailing the presumption that positive cash flows are expected in the future. They conclude by stating these technological revolutions are difficult to forecast until after the fact and that uncertainty plays a key role in stock price volatility.

Xu (2006) agrees that the biotechnology industry is characterized by information uncertainty that causes capricious market expectation revisions. He acknowledges that more disclosure of uncertain information may fail biotech firms to benefit from information disclosure as share price volatility is found empirically positively correlated with information asymmetry measures. Furthermore, he finds that information uncertainty is a function of a drug's development advancement, the nature of R&D progress (high-risk and the typical time it takes a drug to go from the laboratory to the marketplace), and the "hardness" of the news. Xu references Francis et al. (2005) in his conclusions that information uncertainty can explain the post-announcement drift as investors react more slowly to information that indicates a future with ambiguity. He also finds capricious market response associated with R&D alliance announcements and R&D strategy in terms of portfolio diversification. Xu concludes by stating that there should be a reliable and cost-efficient way to disclose R&D related activity as share price volatility has a component driven by investors' capricious response to released uncertain information about firms (some non-financial disclosures are mandated by the SEC, but not all). Information uncertainty, although related to R&D, can be classified as its own ancillary variable affecting returns surrounding Phase III clinical trial results, however it is difficult to quantify.

Baker and Wurgler (2007) conclude that "stocks of low capitalization, younger, high volatility, non-dividend paying, growth companies, or stocks of firms in financial distress, are likely to be disproportionately sensitive to broad waves of investor sentiment," where sentiment is a belief about future cash flows and investment risks that are not justified by the facts at hand (sentiment-based investor are speculative and irrational in their view). Bulger and Wurgler make an assumption that rational investors, or arbitrageurs, are not aggressive in betting against sentimental investors because of high risk and that stocks with higher transaction costs (like the

types mentioned above) have higher transaction costs. They discuss various influencers on levels of positive and pessimist sentiment (beyond investors having more propensity to speculate on future cash flows of specific stocks) to construct an operational sentiment index: investor seasonal mood, young retail investor involvement, mutual fund flows, trading volume (and IPO trading volume), option implied volatility, debt and equity issuance, and insider trading. They find that speculative stocks in their data pool have lower future returns than bond-like stocks, confirming their sentiment-driven mispricing views. Below illustrates their belief of the relationship between sentiment and arbitrage:

Figure 1. Cross-sectional effects of investor sentiment. Stocks that are speculative and difficult to value and arbitrage will have higher relative valuations when sentiment is high.



(Baker and Wurgler, *Investor Sentiment In The Stock Market*, 2007)

Hypothesis Development:

As referenced in the literary review, there are several “soft” variables influencing biotechnology stock price returns that run alongside equally measureable factors like market capitalization and R&D expenditure value-to-market value. Information uncertainty, information rate of release, number of patents, specific strategic alliances, and human capital all resemble types of soft variables. Xu (2006) makes the point that share price volatility is found empirically positively correlated with information asymmetry measures, but is only able to collect 23 data points. This shows the difficulty in quantifying soft variables in general to be able to properly compare firms. Xu does make the case that the nature of biotechnology R&D progress is the major influencing factor when firms decide on reporting (R&D progress updates can create dramatic positive or pessimist sentiments). Since this study focuses specifically around Phase III results, I intend to represent and capture some of the soft variables, largely revolving R&D-related activity, in the R&D expenditure value-to-market value ratio between firms.

Titi (2014) agrees with Hand (2001) in that R&D absorbs the book-to-market effect, where high book value represents less returns in the Fama-French three-factor model. This is due to the fact that aggregate balance sheet and income statement variables, such as shareholder equity and net income, are biased measures of the economic position and earnings of a biotechnology company under U.S. GAAP. According to both Titi and Hand, higher R&D expenditure (in relation to market value) corresponds to higher returns. Titi (2014) and Chan et al. (2001) rationalize this by stating stocks with high R&D to market ratios tend to be stocks with poor past returns and the market discounts heavily the likelihood of their future recovery by underreacting to manager’s signals. This study intends to utilize R&D intensity alongside company market values (market capitalization).

Wrapping this all together, this study intends to prove that biotechnology stock price upside or downsize surrounding Phase III clinical trial results are inversely proportional to their market capitalization size, directly proportional to their R&D expenditure value-to-market value, and directly proportional to success or failure of FDA results. Further relationships like pre-announcement insider trading or post-negative-announcement stock drift will be investigated (by collecting daily average percent returns) as they provide evidence of investor sentiment echoed by previous studies in relation to various soft variables like insider trading and information uncertainty. The Fama-French model/regression will be utilized to obtain cumulative abnormal company stock returns (abnormal returns that include the day prior and day following announcement day). A secondary regression will test firm-specific attributes influencing these abnormal returns.

Methodology:

The study population consisted of various biotechnology and pharmaceutical companies that issued Phase III clinical trial announcements between January 2015 and December 2015 (the term "biotechnology" typically refers to both biotech and big-pharma stocks). To obtain these companies, the "Drug Trial News" press release section at Drugs.com was utilized. The keywords "Phase 3 results" and "Phase III results" were used to narrow down the search. In further filtering search results, press releases containing "company announces topline results" or "primary endpoint met/was not met" were singled out as they were directly relevant and more likely to contain Phase 3 information investors were not exposed to previously. All companies in the study had to be actively trading on the New York Stock Exchange and be the sole sponsor of their clinical trials. Any press release with data announcements or interim results were ignored. Unfortunately, Drugs.com did not provide as many data points as initially expected; companies

(or company names) that completed Phase 3 trials in 2015 were subsequently collected on clinicaltrails.gov to further build the data set. These company's Phase 3 press releases (and results) where obtained on MarketWatch.com's company press release section (similar filtering parameters mentioned previously were applied). Conducting a general Google search helped obtain several more clinical trial press releases; the following filters were used: "phase 3 results from: 2015" and "phase 3 results do not meet primary endpoint from: 2015." 3 search-pages worth of results were scanned.

Phase III trial outcomes were logged as either positive or negative (0 for positive and 1 for negative); positive trials if they were the first randomized Phase III clinical trial for a given indication in which there was a statistically significant improvement in their primary endpoint (Rothenstein et al., 2011). Orphan drugs and drugs that received accelerated approval were excluded. Negative trials were classified as the first randomized phase III trial that failed to show a statistically significant difference between treatment arms in the primary endpoint, and the drug had not received FDA approval for any indication (negative trials on a specific drug will only be included once) (Rothenstein et al., 2011). The company's stock ticker, Phase 3 press release news date, and prior quarter (prior to press release, i.e. "2015Q2") were also logged.

Prior quarter information (the prior quarter in terms of FDA clinical trial announcement day) was important; the natural log of each company's prior quarter market capitalization and prior quarter R&D-to-Market Value (%) were obtained and represented information investors has access to before Phase III news release. These numbers were obtained by utilizing the Wharton Research Data Services database (Compustat).

Yahoo was subsequently searched to obtain daily stock percentage movements for each company starting from January of 2014 and ending in May of 2016. The average daily stock

price movement from -1 year to day -2 (prior to announcement - “period 1”) was calculated for each of the 35 companies (8 companies were repeated as they had multiple Phase III trials in the data set). Day 0 was defined as the day active trading could take place following the announcement; if the announcement took place before the stock market closed, the current day was day 0, if it took place after the market had closed, the following day was day 0 (Rothenstein et al., 2011). The average daily stock price movement (for each company) from -3 months to -2 days prior to announcement (period 2) and from +2 days to +6 months following announcement (period 3) were also collected. Using this data, overall (i.e. all stocks combined) average daily stock movements was calculated in each of the three time frames. Companies that succeeded in their Phase III trials and failed in their Phase III trials were averaged separately for further analysis. Daily stock movements from the three periods where utilized for the analysis of insider trading (periods 1 and 2) and post-announcement drift (period 3).

After obtaining the aforementioned information, the abnormal returns for each company (some companies had multiple abnormal returns based on several Phase III release dates) on trading day -1, trading day 0, and trading day +1 relative to announcement were calculated; the summation of these abnormal returns represented the cumulative abnormal return during the event window {-1 to +1}. To get these abnormal returns for three separate days, the actual stock price movement (easily obtained via Yahoo Finance) was subtracted from the predicted stock price movement. As referenced in the literary review, the most straight-forward way in obtaining predicted returns on any given day is by utilizing the Fama-and-French regression model. One year’s worth of each company’s stock price movement (daily percentage movements across “period 1”) and Fama-and French daily SMB, HML, and Mkt-Rf historical factors (obtained online here) were regressed to generate the three betas or coefficients that could be multiplied by

their specific (day -1, 0, and +1) factors; these values were then added together to calculate the predicted daily return.

Cumulative abnormal returns for each company were then tested for significance given specific-firm characteristics using a second regression. The natural logarithm of market capitalization, the R&D expenditure value-to-market value (R&D intensity), and the FDA success or failure factor (0 or 1) served as dependent variables in the regression.

Results and Discussion:

Upon conducting the second regression with 42 data points, the following coefficient results were obtained for news type, market capitalization, and R&D intensity:

	Coefficients	*Standard Error*	*t Stat*	*P-value*
Intercept	0.109953052	0.080503865	1.365810855	0.180028285
News Type (0 or 1)	-0.030974272	0.037278924	-0.830878913	0.411232369
LN of MKT CAP	-0.009600941	0.007194317	-1.334517462	0.18997617
Prior Quarter R&D-to-Mkt Value	-0.433246237	0.640375541	-0.676550258	0.50278895

As indicated by each of the P-values, each factor within the regression was not statistically significant. The three hypotheses outlined below were thus unverified:

H1: Biotechnology stock price upside or downsize surrounding Phase III clinical trial results are inversely proportional to their (log) market capitalization size.

H2: Biotechnology stock price upside or downsize surrounding Phase III clinical trial results are directly proportional to their R&D expenditure value-to-market value.

H3: Biotechnology stock price upside or downsize surrounding Phase III clinical trial results are directly proportional to the type of press release (success or failure).

Upon further analysis, several companies within the data pool seemed to have significant (more than 5%) price movements in the opposite expected direction based on their Phase III news release type (success or failure); this indicated that investor psychology and subtler details within the drug trial's results had a significant role in shifting stock prices beyond metrics examined in this study. A subsequent regression sought to provide statistically significant results when removing 9 outliers (5%+ movements in the seemingly wrong direction based on news type). Below shows the results of the regression conducted:

	Coefficients	*Standard Error*	*t Stat*	*P-value*
Intercept	0.123523775	0.076679375	1.610912656	0.117335568
News Type	-0.104461702	0.033339327	-3.133287644	0.003761423
LN of MKT CAP	-0.009996381	0.006693458	-1.493455307	0.145427367
Prior Quarter R&D-to-Mkt Value	-0.140024243	0.546430925	-0.256252413	0.799448868

One factor within the second regression model was statistically significant with regards to stock price movement during the event window: news type. A coefficient of -.1044 represents a 10.44% difference between average success and average failure in cumulative abnormal returns.

As mentioned previously, pre-announcement insider trading and post-announcement drift were also investigated. Using all 42 companies, average daily stock price movement was obtained during three time frames for each company: from -1 year to day -2 prior to announcement (period 1), from -3 months to -2 days prior to announcement (period 2), and from +2 days to +6 months following announcement (period 3). Below illustrates the average (average of 42 averages) daily price movement for any given stock. Averages for just companies that had positive Phase 3 results and for companies that had negative Phase 3 results during each time frame are also calculated and shown:

All 43 Companies:	0.03%
Phase 3 SUCCESS Companies only:	0.01%
Phase 3 FAILURE Companies only:	0.06%

Period 1

All 43 Companies:	-0.03%
Phase 3 SUCCESS Companies only:	-0.03%
Phase 3 FAILURE Companies only:	-0.04%

Period 2

All 43 Companies:	-0.13%
Phase 3 SUCCESS Companies only:	-0.05%
Phase 3 FAILURE Companies only:	-0.29%

Period 3

Periods 1 and 2 were used to depict the possibility of insider trading. To provide proof of that, average daily stock price percentage movements during period 2 had to outperform those calculated in period 1 (for "success" companies). As seen in the results above, period 2's daily movements were typically negative for the 42 stocks investigated compared to positive percentage movements seen in period 1; insider trading was not determined to be a factor in this study's small data set. Post-negative-announcement drift, conversely, was determined based on the data; period 3 illustrates how the average stock had a -0.29% daily percentage decline. The phenomenon of post-negative-announcement drift presents the case for the slow realization of future ambiguity evident in the biotechnology sector and the high risk arbitrageurs don't take in countering sentiment-based investors.

To conclude with a short discussion, the results of this study were quite disappointing as they provided little statistical evidence in verifying the hypotheses. Collecting abnormal returns during the event window proved cumbersome as it was extremely difficult to determine if press releases truly provided pivotal information never disseminated before. To build upon this research, it would be ideal to utilize a different regression model to generate cumulative

abnormal returns; research outlined in the literary review, for instance, suggested that book-to-market value was absorbed by biotechnology R&D, but that was not put into practice in this study. There seemed to be many stocks in the data set moving in unexpected directions; analyzing actual press releases is something critical for future elaboration.

Conclusion:

We calculated cumulative abnormal returns of 35 different biotech companies using the Fama-and-French model. These cumulative abnormal returns served as the dependent variable in subsequent regressions searching the significance of R&D, market capitalization, and Phase III news type on event window stock price movement. Although most results did not show statistical significance, we were able to provide evidence for post-negative-announcement stock drift. In a future study, more observations will have to be utilized and press releases would have to be investigated for nuances that drive stocks in the opposite expected direction.

References:

Baker, M., & Wurgler, J. (2007). Investor sentiment in the stock market.

Bastin, V., & Hubner, G. (2006). Concentrated Announcements on Clustered Data: An Event Study on Biotechnology Stocks. SSRN Electronic Journal, 35(1).

Chan, Louis KC, Joseph Lankonishok, and Theodore Sougiannis. (2001). "The Stock Market Valuation of Research and Development Expenditures." The Journal of Finance 56.6. 2431-2456.

Chan, W. (2003). Stock price reaction to news and no-news: Drift and reversal after headlines. Journal of Financial Economics, 70(2), 223-260.

Daniel, K.D., Hirshleifer, D., Subrahmanyam, A. (1998). Investor psychology and security market under and over-reactions. Journal of Finance 53, 1839–1885.

Fama, Eugene and Kenneth French. (1993). "Common Risk Factors in the Returns on Stocks and Bonds." Journal of Finance. 33:1, pp. 3–56.

Francis, J.; R. Olsson and K. Schipper. (2005). Accounting anomalies and information uncertainty. Working paper. MIT, Duke University, Financial Accounting Standard Board (U.S.)

Hand, J. (2001). The Market Valuation of Biotechnology Firms and Biotechnology R&D. SSRN Electronic Journal, 12.

Hong, H., Lim, T., Stein, J. (2000). Bad news travels slowly: size, analyst coverage, and the profitability of momentum strategies. Journal of Finance 55, 265–295.

Hong, H., Stein, J. (1999). A unified theory of underreaction, momentum trading and overreaction in asset markets. Journal of Finance 54, 2143–2184.

Lee, C.M.C., Swaminathan, B. (2000). Price momentum and trading volume. Journal of Finance 55, 2017–2069.

Malkiel, B. (2003). Efficient Market Hypothesis. Finance, 17(1), 127-134.

Pastor, L., & Veronesi, P. (2005). Technological revolutions and stock prices (No. w11876). National Bureau of Economic Research.

Rothenstein, J., Tomlinson, G., Tannock, I., & Detsky, A. (2011). Company Stock Prices Before and After Public Announcements Related to Oncology Drugs. JNCI Journal of the National Cancer Institute, 103(20), 1507-1512.

Titi, A. (2014). The Effect of R&D Expenditures on Stock Returns, Price. A study on biotechnological and pharmaceutical industry in the US market.

Weintraub, A. (2015, July 21). Biotech Investing Hits An All-Time High--But Is It A Bubble? Retrieved December 23, 2015, from http://www.forbes.com/sites/arleneweintraub/2015/07/21/biotech-investing-hits-an-all-time-high-but-is-it-a-bubble/

Xu, Baxia. (2006). “R&D strategy and stock price volatility in the biotechnology industry.” Review of Accounting and Finance 5.1. 59-71.