Unwanted Side-Effects: Idiosyncratic Volatility and M&A Activity in the U.S. Biopharmaceuticals Industry

Ceilidh Meagher & Anton Truvé

(40751 & 22356)

Stockholm School of Economics: Spring 2016

Supervisor: Francesco Sangiorgi

Master of Science in Finance Thesis

Abstract

In this paper we use the disaggregated approach as outlined by Campbell et al. (2001) to study the volatility of firms within the U.S. pharmaceutical and biotech industry at the market, industry and firm levels. We construct volatility series for a period of 26 years from 1990 to 2015, and find that as expected, there are high levels of idiosyncratic volatility for the average biopharmaceutial firm. There are large variations in volatility over the period, with significant spikes at events such as milestones within regulation and financial crises. There is a high correlation between the series. We attempt to relate the identified volatility series to the booming M&A activity within the industry, and we find a significant relationship between M&A activity and firm level volatility.

1 Introduction

In this thesis, we seek to explore the potential effects of the rapidly changing business environment of the pharmaceutical and biotechnology (biopharmaceutical) industry. Although in the past few decades many industries have experienced great changes in structure or operational environments, one could argue that one industry facing some of the most radical and acute changes is the pharma & biotech industry. A defining characteristic of the industry is that the innovations and discoveries produced by firms have a direct impact on the lives of human beings. Since there is a direct connection between the industry and the overall health of consumers, the pharmaceutical industry in the United States is subject to direct supervision and stringent regulation. This supervision and regulation come in the form of strict drug approval processes required by government agencies (namely the FDA, or Food and Drug Administration) and protection of unique intellectual property rights (through patenting and market exclusivity agreements), both of which are often initiated at the end of increasingly expensive and extremely research-intensive innovation processes on the part of the pharma and biotech corporations. Thus, the pharmaceutical industry faces a unique challenge in the sense that it is research and technology-intensive, and the technologies used to develop new drugs and treatments are evolving and progressing at a pace that far exceeds the pace at which industry regulation progresses. In a later section, the nature of the pharma & biotech industry will be described in order to examine how the changing nature of the industry business environment may effect the stock price volatilities of pharma & biotech firms.

The current situaton in the pharma & biotech industry could be described as being in a state of flux. Throughout the last fifteen years, the industry has been rapidly changing. In fact, prior to the late 1990's, the pharmaceutical industry could be described as being dominated by a few major firms, incorporating organic research and development departments, with a focus on discovering medical cures and developing important drugs that could then address the pressing health concerns of the time. However, as many important drugs were being developed at a rapid pace, more capital was required to fund research for additional new drugs, which would hopefully then lead to a windfall of cash from

patents and market exclusivity for these important new cures. It was fairly standard that companies would spend roughly between 17% and 20% of their revenues investing back into their own research and development efforts. As regulatory efforts increased however, pharmaceutical firms began facing additional barriers to both drug development and drug approval. Furthermore, once patents and market exclusivity for a firm's most profitable drug were to expire (often many firms have only a few or even a single drug driving the vast majority of its revenues), firms faced the possibility of generic versions of their drug entering the market, meaning their drug would no longer be the only treatment for a given condition available for purchase by consumers and that generics would absorb revenues instead.

Although there were certain difficulties faced by major pharma & biotech firms with regard to drug development, regulatory changes, and market competition, the major firms did still retain certain advantages. The largest pharmaceutical firms such as Pfizer and Johnson & Johnson had both broad (often global) reach with regard to their marketing power and scope, accompanied by significant marketing experience and expertise. Additionally, these firms had vast amounts of capital, cash buffers, and functional existing corporate structures, as well as widely recognizeable brands.

Over the last 15 years, technology (digital, medical, biomedical, etc.) has improved rapidly. Important medical cures and drugs have become increasingly harder (and exceedingly more expensive) to discover. Additionally, many of the illnesses requiring medical cures via pharmaceutical treatments are often very rare diseases, with not enough people globally suffering from the illness to warrant such extensive research expenditures to discover a cure (in terms of potential future profits). Patent expirations and losses of market exclusivity rights for certain drugs have many firms facing the potential loss of their revenue-driving products, upon which they rely for a vast majority of their profits. The regulatory environment has become even more stringent, expensive and unforgiving as drugs and treatment methods come into question for unwanted side-effects. This combination of challenges facing the pharmaceutical industry have caused the industry on the whole to undergo a gradual restructuring, that in the last 15 years has truly taken hold and begun to define the nature of the process for developing new drug treatments

and medical innovation. The pharma industry has shifted from previously being a diverse array of independent, smaller firms who are constantly investing in research and development in order to improve and fill their product pipelines with profitable new innovations, to a conglomeration of major firms participating in a frenzy of mergers and acquistions (often acquisitions of much smaller pharma or biotech firms), in order to either gain intellectual property rights to a profitable treatment with existing market exclusivity that may already have been developed. Many of these deals are motivated by the desire to avoid the patent cliff, or obtain a source of sufficient products under development that the acquring firm can fill the holes in its own product pipeline. As major pharmaceutical corporations with broad marketing reach and economies of scale and scope look to supplement their existing, but often dwindling, product pipelines, firms are falling farther and farther into the tactic of acquiring smaller firms with technological innovations and often paying a hefty premium for such acquisitions. Effectively, this frenzy of mergers and acquisitions activity dominating the current business environment of the pharmaceutical industry has led to the outsourcing of research and development from the R&D departments of the major pharma firms that used to rely on their own in-house departments for new products, to smaller firms who are usually in the process of developing products (meaning that there is no real guarantee for regulatory approval and market success of the products they are currently developing). This leaves the pharma industry in a difficult position. These major pharma firms continue to buy up smaller firms focusing mainly on R&D with no guarantee of success, and pay premiums for them, comparable to these major corporations buying options. Their acquisitions can either have extreme positive payoffs (if the drugs from the new firm get governmental approval and guaranteed market exclusivity), or they can fail to yield revenue-driving innovations.

With the nature of business and innovation in the pharma industry changing so much over the last 15 years and with those changes continuing to occur on a daily basis, we aim to see whether those changes in the industry have had larger effects on the pharmaceutical industry stock market as a whole. For example, we examine whether or not the idiosyncratic volatility within the pharmaceutical industry has increased over the last fifteen years on the industry-level, as well as examining whether individual pharmaceutical firms have

become more volatile at the firm-level. We aim to see whether or not increases in total volatility for the pharmaceutical industry and the firms within it are due to increases in systematic risk, or increases in idiosyncratic risks both at the industry and at the firm-specific level. We also aim to provide some reasons as to why an increase in idiosyncratic volatility within the pharmaceutical industry actually matters. Although one could argue that investors could diversify away idiosyncratic volatilities by actively managing their portfolios, many are not actively monitoring their investments, and leave themselves and their portfolios susceptible to potential loss as a result of increases in idiosyncratic volatility. Furthermore, we argue that it is important to examine volatility trends as one could theoretically form feasible and profitable trading strategies from idiosyncratic volatilities.

In this paper, we isolate the volatility series of gross and excess returns of the market, the biopharmaceutical industry, the average biopharmaceutical firm, and the average "big pharma" firm. After obtaining these results, we analyze the differences in the volatilities at the different levels and we seek to help explain their evolution over time.

2 Hypotheses and Relevant Empirical Testing

It is our intention in this paper to examine whether or not idiosyncratic volatility has increased over time within the pharmaceutical industry. Since Campbell et al. (2001) were able to conclude that there was a trend increase in idiosyncratic volatility for individual firms relative to market voltility, they were able to attribute the increase in firm-level volatility to idiosyncratic volatility increases, rather than to increases or fluctuations in the overall stock market's systematic volatility. In fact, as the increase was shown to be mainly due to firm-level idiosyncratic volatilities, they conclude that it would require a larger number of stock holdings within the market in order to achieve diversification of a portfolio, given that the serial correlations between the individual stocks had declined. What we intend to examine is whether or not, at the industry and firm levels, there has been a similar increase in idiosyncratic volatility. Given the rapidly changing nature of the business environment within the pharmaceutical industry, it is our hypothesis that the more complicated, riskier structure of the current market (with its growing market

for mergers and acquisitions, outsourcing of product and drug research and development, and the formation of global partnerships in an aim for firms to achieve economies of scale and scope through marketing efforts and reach), that there will in fact be an increase in the level of idiosyncratic volatilities over time. We believe that this time-varying increase in idiosyncratic volatility will be present not only at the firm level (which essentially, Campbell et al. (2001) found in their research), but also at the industry level, due to the increased uncertainty of expected future profits for major and smaller pharmaceutical firms who are struggling to maintain intellectual property rights and market exclusivity, as well as stable product pipelines.

Furthermore, our second aim is to test the relation between the increased M&A activity within the industry and volatility. There is mixed evidence from practitioners and researchers suggesting that on one hand, volatility itself may spur M&A transactions, and that M&A transactions are in fact more successful in uncertain times. Gatti and Chiarella (2013) outlines another hypothesis, namely that M&A activity increases with volatility, but acts in a stabilising manner to the industry since firms could be thought of as hedging their bets through acquiring smaller firms. On the other hand, acquiring small firms could be thought of as buying options, which may have a huge impact if the drug they are developing succeeds, but may also fail and yield no value at all, and thus increase volatility. To test this relationship we will run regressions where we try to explain volatility based on the number and the total value of the deals on both an annual and a monthly basis.

Overall, because of diversification effects, we expect the average market volatility level to be the lowest of the four series we isolate, with the Pharma Index having the next lowest level, but for the big pharma volatility series to have a higher level than the industry, and we expect the average pharma firm-level to have the highest volatility over time. As was found by Campbell et al. (2001), we also expect an increase in the volatility of the average firm over time, meaning that there might be some form of trend showing a progressive increase in the level of volatility for firms within the pharma industry. Lastly, given the results we obtain from the volatility decomposition, we expect to see some sort of significant effect of industry M&A activity on the volatility behavior of our series, especially at the firm and industry levels. Although as mentioned earlier, there are theories from

researchers arguing that such activity can act as a stabilizing force in the market, we would initially expect that the rapid increase in this activity would actually yield a more volatile environment within biopharmaceuticals. Furthermore, we will also examine whether or not industry-specific product approval success rates have some type of significant impact on the volatility behavior of the average firm, which again we would expect to increase volatility.

3 Related Literature

Our paper seeks to test a hypothesis about stock return volatility in a specific industry: the biopharmaceuticals industry. However, not much has been written about this exact topic in the canon of premier academic finance literature. Thus, our idea is to combine notions regarding our specific topic and subsequent hypotheses, by extracting relevant information about both idiosyncratic volatility, the prevailing nature of the pharmaceutical industry's business environment, and the process of developing or acquiring "blockbuster drugs", patents, or market exclusivity in order for corporations to ensure future profits.

Because our paper revolves around examining the increase in idiosyncratic volatility within the pharmaceutical industry, both at the industry level and at the firm level, we can isolate the aforementioned Campbell et al. (2001) as being a sort of empirical backbone for a large part of our research and empirical analysis. The paper, *"Have Individual Stocks Become More Volatile? An Empirical Exploration of Idiosyncratic Risk"*, examines the hypothesis of whether or not idiosyncratic volatility has increased in the past on three different levels: the individual firm level, the industry level, and the market-wide level (across the entire market return). Campbell et al. use a disaggregated approach to study the volatility of common stocks over a period of thirty-five years (1962-1997) at the three different levels listed above. What Campbell, Lettau, Malkiel and Xu subsequently examine after isolating their volatility series, is whether or not the correlations between individual stocks have increased, whether the standard market model retains its explanatory power for a typical stock, and if diversification efforts must be increased by investors to help achieve the same level of diversification as in previous years. Finally, Campbell et

al use their findings to test whether or not the volatility measures move together cyclically or countercyclically, and if the three separate volatility series can be used to predict GDP growth, as well as the movements of each other.

Campbell et al. (2001) argue that there are various reasons to be interested in all three volatility series, as opposed to just being interested in the volatility series of the aggregate market return. They note that the overall market return is only one component to the total return of a single stock, and that industry-level and idiosyncratic firm-level shocks comprise two other components of that same individual stock's return. Without taking proper notice of these two components, different types of investors could be adversely affected, as diversification may become more complicated for investors with large holdings of certain individual stocks or stocks only within a certain industry. Furthermore, pricing errors could occur as a consequence of larger idiosyncratic firm-level volatility (with specific importance to arbitrageurs), and option prices also depend on the total volatility of an individual stock return (which Campbell et al conclude is comprised of all three volatility series components).

The authors use CRSP daily stock return data for the given thirty-five year period to construct monthly sample variances of the market return, industry-level return, and firm-level return. They elect to follow the methodology first employed by notable researchers such as Merton (1980) of constructing a variance decomposition that does not require the estimation of covariances or betas for industries or firms. Essentially, electing to construct this type of model means that the authors employ a non-parametric model to describe the historical movements in the three volatility series. Parametric models are far more important for forecasting future time-series variations, rather than describing historical movements.

The important and most notable conclusions of Campbell et al. (2001) are that although they find that the volatility of the market as a whole did not increase over their specified thirty-five year period, the firm-level idiosyncratic risk and uncertainty has certainly increased over the same period. This means that the correlations between individual stocks has not only decreased, but that the typical market model loses explanatory power in describing the return of a typical common stock. Through examining the variations

of the volatility measures around their long-term trends, they also find that the three individual measures are not only positively correlated with each other, but they are also autocorrelated, and Granger-causality tests yield the finding that market volatility tend to lead the other two volatility series. With regard to how these findings could relate to the larger picture of the market in terms of looking at the results from a macroeconomic approach, the authors find that all three of the volatility measures significantly increase during economic downturns, as well as lead recessions. Futhermore, the industry-level volatility reduces the significance of other forecasting variables.

Campbell et al. (2001) serves as the inspiration for much of our own empirical analysis. We follow their methodology of the variance decomposition, in accordance with the weighted average non-parametric approach. In our empirical analysis, we perform many of the same tests, yet we differ by focusing our efforts on a single industry. Since we are, in this paper, looking specifically at the pharma & biotech industry, after gathering results surrounding volatility series for the market, industry, and firm levels, we can attempt a more in-depth analysis of the industry and firm-level findings. For example, we will attempt to employ regression models to help explain our volatility series findings based on the booming M&A market in the industry, thus we introduce different factors which may hold explanatory power for the industry and firm volatilities. As such, we examine whether the number of mergers and acquisitions within the pharmaceutical industry have any significant relation to the volatility series, while controlling for some macro characteristics.

Following up on Campbell's work, Goyal and Santa-Clara (2003) find that the variance of the market has no forecasting power for the market return. However, they find evidence of a significant positive relation between average stock variance and the return on the market, suggesting that idiosyncratic risk actually gets priced, in contrast to theories suggesting that only systematic risk will be priced, since investors can always diversify. Though Goyal and Santa-Clara's findings are at odds with much of the literature, there are several asset pricing models proposed by other researchers, often building upon Douglas (1969) and Levy (1978), that do take idiosyncratic volatility into account. One example is Barberis and Huang (2001), where a model in which investors are loss-averse over changes

in the individual stocks owned is proposed, obtaining a relationship between expected returns and idiosyncratic risk. Another is Bessembinder and Seguin (1992). In Goyal and Santa-Clara (2003)'s paper, the main explanation of the results is based on non-traded risky assets (as pioneered by Mayers (1976))such as human capital and private businesses, which would give the obtained result if these assets are related to the total risk of individual stocks.

Another important paper for our thesis, is that of Mazzucato and Tancioni (2005): *"Stock Price Volatility and Patent Citation Dynamics: The Case of the Pharmaceutical Industry"*. Not only does their work heavily reference Campbell et al. (2001) which is discussed above, but it builds on the idea of increased industry-level volatility within the pharmaceutical industry. Essentially, what Mazzucato and Tancioni (2005) do is create a link between what they term "innovation factors" and volatility in the pharma industry. Their efforts are to try and understand the dynamics of stock price volatility by identifying a causal relationship between stock price and firm-level innovation. They create their innovation factors as reflection of patent information. They ultimately weight patents by the number of citations they have, essentially letting the citation-weighted patents serve as an indication of whether or not the patent was actually important for innovation and firms' future profits. As another innovation factor, they identify Research & Development expenditures for individual firms. In an earlier paper, Mazzucato found that idiosyncratic risk tends to be higher in periods of the industry's life-cycle where innovation is perceived as the "most radical", and this 2005 paper not only builds on this previous finding, but attempts to explain radical innovations' effect on volatility and persisting idiosyncratic risk. There is some overlap with the theories on R&D spending presented by Golec et al. (2005) and the work of Hall et al. (2005) on patent citations.

Through a three-step empirical process, the authors look at the volatility of the market as a flow variable, then test whether a statistical relationship between idiosyncratic risk and their innovation variables could be detected, concluding with a test of the "rational bubble hypothesis" found in Pastor and Veronesi (2004). Although the first and third steps of their empirical work is not quite relevant to our specific empirical work in this paper, we do take inspiration from them through their efforts to build on Campbell et al.

(2001)'s findings and try to draw up a direct link between increased idiosyncratic volatility within the pharmaceutical industry and actual firm-level innovation efforts. We attempt to perform a similar type of explanatory analysis in our paper, after obtaining the results of our volatility series. We hope to introduce explanatory factors that bear relevance to the current prevailing business environment within the pharmaceutical industry, i.e. that of excessive mergers and acquisitions being undertaken by firms in hopes of using the transaction as a means of protecting intellectual property and market exclusivity rights, or obtain global marketing reach. We believe we must factor the most recent prevailing business environment into account because the pharmaceutical industry is a prime example of a technology-induced rapidly changing industry. As the technology improves at such a fast rate, as legislation to protect consumers and pharmaceutical developers lags behind, and as costs to develop new "blockbuster drugs" increases dramatically, the industry faces new challenges that have forced firms to adopt new business practices and operations as a means of survival.

In a 2005 paper, Matthew Higgins and Daniel Rodriguez examine how firms in the pharmaceutical industry are using mergers and acquisitions as a means of oursourcing research and development efforts. They explore both the motivations behind the acquisitions and the returns experienced by the firms participating in such M&A activities. Higgins and Rodriguez (2006) find that often the returns to an acquisition, positive, negative or zero, depend on the acquirers' access to information about the target firms, the initial motivation driving the firm to acquire the target firm, and the capacity for the acquiring firm to successfully integrate the operations of the target firm into its corporate structure and operational activities. The authors find that biopharmaceutical firms are fully capable of successfully outsourcing research and development through acquisition activities, but the success of the acquisition often heavily depends on the information available to the acquiring firm in the pre-acquisition period, and the negotiating position of the acquiring firm. Additionally, the authors find that firms looking to obtain "product pipeline improvements" are significantly more likely to undertake acquisitions of research-intensive biopharmaceutical firms or biotechnology firms. Often this pressure to improve product pipelines can deteriorate the negotiating position of firms looking to make an acquisition

and lower negotiating power can often entail the acquring firm paying an excessive premium for the target firm. Perhaps most significantly, Higgins and Rodriguez identify what they determine to be the overall driving factor behind much of the M&A activity occurring within the pharmaceuticals industry: "the aging of the overall industry profile". They find that the total number of "exclusivity years" for individual patented products has fallen significantly between 1995 and 2001, and that the overall rate of productivity in the pharma industry (in terms of creating new, FDA-approved, patent-protected drugs) has thus fallen to levels that drive firms to undertake acquisitions in hopes of replenishing their product pipelines to ensure future profits and returns to shareholders. They outline the four most common methods used by major pharma firms to respond to the declines in R&D: firms can acquire smaller pharma or biotech firms, they can undergo large horizontal mergers (in order to gain economies of scale and of scope), they could acquire existing or mature products (through license agreements that would grant them both market exclusivity and patent-protection for the remaining years on the patent), or pharma firms could organically increase internal research and development. Expanding along the lines of acqusitions and motivations behind them, the Higgins and Rodriguez (2006) also propose that firms can actively make acquisitions today in hopes of replenishing their product pipeline and profits in order to give them a superior negotiating position for acquisitions in the future. The authors examine the unique features of the biopharmaceutical industry in order to help explain the propensity for pharmaceutical and biotechnology firms to actively seek out or participate in mergers and acquisitions activities in the present-day market.

Higgins and Rodriguez (2006) stress the fact that pharma firms are mainly looking to replenish their product pipelines. The big question is how they go about doing so. It seems that in the current pharma industry, the answer has become for firms to either make acquisitions or be acquired. The authors find that if a firm is already struggling to ensure its product pipeline, then that firm is far more likely to engage in an M&A transaction. The trouble is ensuring that the acquiring firms realize positive benefits from the acquisitions.

Another paper with a similar examination of M&A activity in the pharma industry is that of Danzon et al. (2004).In their paper *"Mergers and Acquisitions in the Pharmaceu-*

tical and Biotech Industries", the authors more closely examine the determinants of the M&A activity in the industry and firms' propensity to participate in such activities based on their uniquely constructed "Desperation Index". The authors differentiate between the types of firms that exist in the industry, such as larger or smaller firms, Essentially, their findings conclude that larger firms often undergo mergers under the "excess capacity theory of mergers". With that said however, there is added volatility because acquiring firms often pay premiums for targets, or to ensure that their current operations are not deemed as "excess capacity", meaning that if they employ people due to the success of a certain product, they will need to ensure that they have other viable products to sell in the future to justify employing their existing amount of human and physical capital. They identify that being acquired often acts as an exit strategy for smaller pharma or biotech firms, especially if they have products that are mature and far along in the FDA approval and patenting process.

Danzon et al. (2004) identify that firms are susceptible to "the patent-driven nature of a research-based pharma firms' sales", and that "capacity adjustment motives" are also present. Essentially this would involve firms merging to restructure their asset bases, which typically happens in industries that experience shocks due to technological changes or deregulation. The trouble with the pharma industry is that since new drugs are becoming so expensive to create, the capital employed to create them can seem excessive or unnecessary if massive future profits cannot be ensured. Danzon et al. (2004) note that the pharma industry is becoming increasingly concentrated, with the ten largest firms often accounting for roughly half of the industry's sales in the United States. This presents the pharma industry with an interesting and unique dynamic. In fact, with this in mind we take a closer look at these "Big Pharma" firms by creating a volatility series only including these firms to examine whether or not the volatility of their excess returns is significantly different from that of the average pharma firm.

A paper with focus on the M&A market and volatility, though not specifically for the pharma industry is Gatti and Chiarella (2013). The authors perform a study on the characteristics of M&A during uncertain times, i.e. times of high volatility in the market. There are some motives as to why companies would have incentives to pursue

acquisitions in rough times, such as the need to restructure to face a changing market or taking advantage of targets in distress. Gatti & Chiarella find that deals undertaken in high volatility environments deliver a higher median excess return, and they attempt to explain this difference. Their analysis is highly relevant to this paper, though we intend to relate deal activity in a specific sector to volatility, while Gatti & Chiarella focus more closely on the impact of the deal being made in a volatile time on the deal itself.

Bharath and Wu (2005) study the long-run effect of mergers on volatility, and find a run-up in volatility beginning four years before a merger. They provide some evidence that this run-up is consistent with the hypothesis that mergers are the result of industry shocks. They provide a possible explanation being that acquisitions are used as a tool by managers to adress increased volatility and risk. The increase in volatility persists for some period after the merger, and the authors propose that this is consistent with post-merger integration risk, and the time it takes for the acquirer to integrate the target firm. In the case of our research, this would mean that acquisitions are often undertaken when volatility is high, and they would then reduce the volatility of the firm after some period. Since in our study, we do not look at specific firms but at the aggregate of firms, we would then expect that volatility would correlate with acquisitions, and that when mergers are then undertaken, volatility may begin to decrease.

4 Industry Overview: Historical Trends & Defining Characteristics

Several important events for the pharma & biotech industry have taken place during the studied timeframe. We aim to provide a brief overview of the most important ones for this study.

In 1992, the Generic Drug Enforcement Act was passed to address concerns about the approval process for generic drugs. One purpose of the act was to authorize the FDA to prevent companies from manufacturing and selling of generic drugs, if the companies were deemed to be corrupt, or acting in violation of the law. Since the act was passed, the FDA has the authority to examine any aspect of a drug's approval and current distribution and

interrupt the process, either by suspending the application or by withdrawing approval for an existing approved generic drug. The same year, the Prescription Drug User Fee Act was passed, allowing the FDA to collect fees from drug manufacturers to fund the new drug approval process. The stated purpose was among others to speed up the drug approval process. The Prescription Drug User Fee Rates for 2016 are roughly USD 2.4 million for an application including clinical trials, and about half of that sum for an application without clinical trials. The passing of these acts led to both concern and optimism within the industry, which is clearly noted in our data, especially on our graphs of the different volatility series, given that there are large spikes in the volatility of the pharmaceutical industry and biopharmaceutical firm-level volatility.

In 1997, the Food and Drug Administration Modernization Act was passed, reauthorizing the 1992 Prescription Drug User Fee Act and essentially mandating the most wide-ranging reforms in FDA practices since 1938. Among other things, this Act introduced the regulation of advertising of unapproved uses of approved drugs and pharmacy compounding. The act was criticized mainly because of the amount of time, money and effort it would require to be implemented. The noticeable jumps in industry and firm specific volatility for our examined time series shows just how impactful legislative regulation can be in determining returns of publicly traded companies in a particular industry. Since the pharmaceuticals, medications and technologies directly impact the daily lives and health of people within the United States, regulation is tighter and often far more invasive than regulation of another type of industry. However, legislative regulation by governmental authorities and compliance with such regulations on the side of the pharmaceutical firms is often a drawn-out process of give and take, a so called type of governmental/corporate "tug of war", where compliance with any new regulations will inevitably take time, if the regulations are not immediately and directly opposed. This would mean that volatility from these regulations discussed here in this section may persist, due to the fact that it may take time for corporations to adjust to new legal standards and cooperate with higher expectations.

The dot-com bubble in the late 90's had a noticeable impact on the pharmaceutical industry. Though the pharma industry in general was reluctant to embrace the internet,

partly due to the industry's regulatory constraints, many senior pharmaceutical executives were indeed extremely interested in the evolving e-health market. Some bigger firms also invested in these start-ups. When the IT-industry imploded, this also had an effect on especially the larger pharma and biotech firms who had made sizeable investments in what they hoped would become a prosperous future of the e-health market.

The financial crisis in the late 2000's also had an impact on the biopharmaceutical industry. There is research, such as Buysse et al. (2010) and Lerer and Piper (2003) indicating that during a financial crisis, healthcare spending, especially by governments, decreases. It is also clear that during a recession, when funding is hard to obtain and risk is generally avoided by investors, the generally more volatile pharma & biotech industriy, where so many companies are often in a stage where drugs and products are still in development and therefore may not be profiting from their research efforts yet, will be hit hard. It can be noted, that bigger pharma companies are generally more stable given their historically large cash reserves and their patents intellectual property rights for the large majority of blockbuster drugs, but for the average pharmacautical firm the effect is huge.

One aspect of this industry that gives it such a unique and interesting dynamic is its propensity to consolidate. As the costs of drug development increase at such rapid rates, and as the effort and amount of research to discover new life-altering medications increases, firms find themselves in unique situations. Often smaller firms focused on research and development of new medical products lack the marketing scale and scope to reach an audience where their new products could become economically viable and achieve higher sales. Many large biopharmaceutical corporations have more intensive marketing efforts with a much larger global reach and can therefore ensure financial success for their products, but they have focused less on developing new drugs as they begin simply acquiring the intellectual property rights for certain drugs already on the market and already protected by market exclusivity rights, or obtaining rights to drugs that are in the later stages of development and successfully headed down the product pipeline. However, both positions (the ones faced by the smaller firms and the ones faced by the larger firms), leave various types of firms exposed to a higher propensity to consolidate. As the industry continues this trend of consolidation (as it has within the past 26 years especially), uncertainty

surrounding the future of product pipelines, regulatory actions, and corporate strategic decisions may increase volatility within the pharmaceutical industry in the United States even further.

5 Data & Empirical Methodology

5.1 Data Collection

The data used in our empirical analysis is collected from the CRSP database. We obtain returns for all listed firms on the NYSE and AMX exchanges for the period January 1, 1990 to December 31, 2015. In thsis paper, we examine only the pharmaceutical industry and the biopharmaceutical firms within the United States of America. With 25 years of comprehensive data for all (non-industry specific) publicily traded firms on the NYSE and AMX, we initially obtain roughly 40 million individual stock price observations. Whilst obtaining the stock price information, we also obtain the following information for each firm in our dataset: the firm name and its unique CRSP identification code (cusip number), the number of shares outstanding for each date, and the industry identification code. With the above information, we are then able to compute the market capitalizations for each firm at each date, and to sort all of the listed traded firms based on their individual identification code. For the purposes of this paper where we attempt an in-depth examination of the pharmaceutical and biotechnology industries, we are able to sort our firms based on their specific industry classification codes (GICS codes) and analyze for industry-level effects through the volatility series. All raw data data obtained is daily data, and it is then used to form monthly and yearly observations for the volatility series which are subsquently analyzed. Using daily data, volatility cannot be observed on a daily basis, and thus the volatility series formed using the daily data are the monthly volatility series (expressed in annual terms) for market-level, industry-level, and average firm-level volatilities of excess returns and gross returns as well as the yearly volatility series for each. In order to obtain the volatility of excess returns the daily United States 3-month T-bill return rate is collected (treating this as the risk-free rate). This data is then used as our launching

point from which we can calculate the market-level excess returns.

It should be noted that the empirical methodology is comprised of two main parts: the first is our isolation of the volatility series for the returns and excess returns of the market, the biopharmaceutical industry, the average firm level, and then the level of the average "big pharma" firm. Through this first empirical focus, we can ascertain that the pharmaceutical industry and pharmaceutical firms have a higher level of volatility that cannot be simply explained by the systematic risk of the market. Coinciding with the thoughts of Campbell et al. (2001), we are therefore conducting the first part of our empirical work to show that there is some significant idiosyncratic risk both at the industry level for the biopharmaceutical industry and at the individual firm level for the companies operating within the industry. After obtaining results from which we can draw conclusions about this increased idiosyncratic volatility and obtaining our expected results of increased idiosyncratic volatility at the firm and industry levels, the aim of the second part of our empirical analysis is to try and create a factor model that can provide some insight as to what industry-specific characteristics or regulatory concerns the biopharmaceutical industry may possess that could lead to this increased idiosyncratic volatility. In this second part we will focus on the M&A environment, in order to attempt to relate volatility to data on deals in the industry.

In order to successfully perform the second half of our empirical analysis, we need to collect industry-specific data. Data regarding merger and acquisition transactions occurring within the pharma and biotech industry throughout the period of 1990 to 2015 are collected from Bloomberg, using the pharma and biotech industry classifications. In addition to obtaining the actual number of transactions that were announced, we also obtain the total value of the deals that occurred, to establish if the actual size of the deals would have any relation to volatility. The data on the deals is then aggregated on a monthly and yearly basis to calculate number of deals, total deal value, and average deal value for the period. The number of deals announced during our time frame was seen as an important factor because it could be one part of explaining whether or not the market would experience adverse affects as a result of increased consolidation within the pharma industry. Furthermore, depending on the motives for the M&A transactions,

volatility could increase if the market was experiencing more pressure and uncertainty of other firms feeling the need to participate in these consolidation activities. In order to control for some macroeconomic factors such as recessions, National Bureau of Economic Research (NBER) data on recessions dates is obtained.

5.2 Empirical Methodology

For our empirical analysis, we roughly follow the methodology of Campbell et al. (2001). We begin by obtaining the stock price data for all listed firms and sorting it according to date. We calculate the return of the entire market as well as for the entire pharmaceutical industry for each date. This is done by calculating the value of the market by aggregating market weights and noting their daily change. For the Pharma Industry, we sort the stock data according to the industry classification code for biopharmaceutical firms and use the number of shares outstanding and each firm's stock prices to calculate the total value of all the pharma firms in aggregation. We construct an index for both the entire market and one that is specific to the pharmaceutical industry. For the Market Return, as according to Campbell et al. (2001), a weighted average of all returns of each firm listed on the market for each date from 1990 to 2015 is used. Using the share prices and the number of shares outstanding, we calculate the market capitalizations for all specific firm on each day of the specified time period. Using the market capitalizations, we calculate the value of the entire market index by summing the market cap for each firm for a given date. After obtaining the value of our entire market index proxy, we then calculate the weight of each firm in the market. With the firm weights, we calculate the market index return as the weighted average of all the individual firm returns for each date of the dataset. Our market index includes all firms listed and traded in all industries for each date in the time period being evaluated. This breadth of our observations enables us to confidently state that our index is diversified and would not be susceptible to the movements of any particular firm or industry, but rather would give a comprehensive overview of the overall market returns for the dates in which we are interested. After obtaining our market return series, we then calculate the excess return of the market over the risk-free rate of return. From

here we obtain our market excess return series. We sort the firms by both date and GICS codes, extracting only the firms involved in the pharmaceutical industry from our initial market data. After extracting only these biopharma-relevant firms, we then construct our pharmaceuticals index proxy, where we again calculate the market capitalizations of all firms on each date of the observation set (1990-2015). As with the market caps for the market index, from here we create the total value of our Pharma Index, and then compute the return of the Pharma Index as a weighted average of the firm weights within the index, and the actual returns of the firms for each date. We then calculate the excess returns of the Pharma Index as the Pharma Index return less that of the market gross return. It is worth noting that although we have a total of 1,091 individual bipharmaceutical firms listed throughout the twenty-five year period that is the time frame for our data, not all of the firms have data that extend throughout this entire period. In fact, it is only recently that many more biopharma firms have entered the industry and been listed on exchanges. For the first few years of the sample, the number of firms comprising our Pharma Index (179) is much smaller than the number of firms present in 2015 (539). However, our weighted average return of the index accounts for this by assigning different weights to firms over time.

One aspect of the empirical methodology that should be clarified is why we created our own "proxy indices". One could note that there are existing biopharmaceutical indices, for example the S&P 500's Pharmaceuticals and Biotech Index. We wanted our data, however, to be fully comprehensive and representative both of the larger market returns overall but more specifically within the pharmaceutical industry and the intersection of the market and the biopharmaceutical industry we look at in this paper. The existing indices with only pharma and biotech specific firms included firms that were not listed on their broader market index counterparts, meaning that if we had collected data from the S&P 500 Market Index, and then compared this data to the industry-specific index S&P maintains for the pharma industry, there would be a discrepancy in the firm data included, as the industry-specific index includes firms that are not listed on the actual S&P 500 Market Index. We found the same to be true for the NASDAQ and the biopharmaceutical industry specific index it maintains as well. Downloading all of the raw returns data for

each firm in the entire NYSE/AMX exchanges excludes the possibility of not having some of the firms be included in either the market or pharma proxy indexes we created.

Once we have successfully obtained the "excess return series" for both the market and the industry, we then use these series to calculate, in line with Campbell et al. (2001)methodology and the beta-free variance decomposition, the corresponding volatility series. The calculation of the volatility series of the market index entails taking our monthly and yearly excess return series and subtracting the overall mean market return for each monthly or yearly observation. From this, we obtain the residual series for the market excess returns, which, when squared, becomes our volatility series. The same is then done with the pharmaceutical proxy index, using the monthly and yearly series and subtracting the mean of the pharma proxy index's overall return from each observation in both series.

An objective of Campbell et al. (2001)'s paper is to examine the difference in the levels of volatility at the different levels of returns, i.e. the market-wide level, the industry-level, and the individual firm-level. After obtaining the market and industry volatility series, we extract the firm-level volatility series. An examination of all firms in all industries is not warranted, since this paper closely examines the difference in idiosyncratic volatility between the market, industry, and firm levels for the pharma & biotech industry. Using data from firms for all different time periods we obtain the average pharmaceutials firm volatility. For each date between 1990 and 2015, the excess return of each firm is calculated as the difference between the firm return and the return of the pharma index. The same approach is used for the Big Pharma firms.

We refer to the Campbell et al. (2001) paper for a detailed derivation of the return series for each level, however, the overarching goal is to use the return series we identified to produce a time-series of volatility measures for the market, pharma industry, the average Big Pharma firm, and the average pharma firm. Specifically, we aim to produce these time-series volatility measures without estimating betas or covariances for industries and firms. The entire beta-free and covariance-free variance decomposition for each series is detailed in Campbell et al. (2001), however we show a portion of the full derivation below. The starting point for the entire variance decomposition process is the traditional CAPM

model, with the restriction of a zero-intercept:

$$R_{jit} = \beta_{ji}\beta_{im}R_{mt} + \beta_{ji}\tilde{\epsilon}_{it} + \tilde{\eta}_{jit} \tag{1}$$

where $R_{j,i,t}$ is the return for firm j in industry i at time t. For the purposes of this paper, the industry i will be the pharmaceutical industry, and the firm j will be the average pharmaceutical firm. β_{ji} is the beta for the average pharmaceutical firm j with respect to the pharmaceutical industry return, and β_{im} is the beta of the pharmaceutical industry with respect to the overall market return. For a model with this equation, there is a condition of orthogonality, meaning that $\beta_{jm} = \beta_{ji}\beta_{im}$. Additionally, $\tilde{\epsilon}_{it}$ becomes the pharmaceutical industry-specific residual, and $\tilde{\eta}_{jit}$ becomes the average pharma firm-specific residual. If one were to continue with the variance decomposition in accordance with the model laid out in Equation 1, then the subsequent variance decomposition would be:

$$Var(R_{jit}) = \beta_{jm}^2 Var(R_{mt}) + \beta_{ji}^2 Var(\tilde{\epsilon}_{it}) + Var(\tilde{\eta}_{jit}) \tag{2}$$

With the above equation however, the variance decomposition would therefore include estimating betas for the respective factors in the model. Campbell et al. (2001) instead propose the use of what they call the "market-adjusted-return model", yielding the industry and firm specific return series equations:

$$R_{it} = R_{mt} + \epsilon_{it} \tag{3}$$

for industries, while the firm-specific equation is:

$$R_{jit} = R_{it} + \eta_{jit}. \tag{4}$$

The reason Campbell et al. (2001) are able to use the market-adjusted-return model instead of the previously shown variance decomposition model in Equation 2, is that when all of the firms in the market are included into the model, the value of beta can be assumed to be one (under the orthogonality condition). Campbell et al. (2001) then use a beta-

free variance decomposition to the market-adjusted return model with weighted averages across firms throughout the market:

$$\sum_{j \in m} \omega_{jmt} Var(R_{jmt}) = \sigma^2_{mt} + \sigma^2_{\epsilon t} + \sigma^2_{\eta t} \tag{5}$$

here, ω_{jmt} are the firm related weights to the market respectively. Here we clearly isolate the three volatility components on the right hand side of Equation 5, σ^2_{mt}, $\sigma^2_{\epsilon t}$, and $\sigma^2_{\eta t}$ are the volatiliy parameters we estimate in the following steps of our empirical methodology. It is worth noting that because we are using weighted averages of the firms in the market for the market-level return, and weighted averages of the firms within the pharmaceutical industry for the industry-level returns, the covariance terms usually required in a variance decomposition cancel out.

5.3 Estimation of Volatility Components

Using the data described in section 6.1, we estimate the market-, industry-, average firm-, and big pharma-level variances to create our volatility series. Since in this paper we are only interested in the volatility of the pharma & biotech industry specifically, we do not aggregate all of the firms listed on the market (for our market-level returns data) into separate industries. Rather, for our industry-level calculations, we extract only the pharma & biotech firms (according to their GICS codes) and use those firms to make relevant pharma industry-specific calculations. We do folllow the methodology of Campbell et al. (2001) in using the excess returns for volatility component estimation.

The estimation of the volatility components entails using time-series variations of each individual return component within the specified time period t. Therefore, following the methodology, we express the market return's sample volatility in period t (MKT_t) as:

$$MKT_t = \hat{\sigma}^2_{mt} = \sum_{s \in t} (R_{ms} - \mu_m)^2 \tag{6}$$

where μ_m is the mean of the market excess return (R_{ms}) over the sample period being examined. The market returns are the weighted average of the returns of all firms in

the sample we use for our "market index proxy", meaning it is a weighted average of all the firms gathered in our initial dataset from CRSP (all firms listed on the NYSE and AMX between 1990 and 2015), keeping in mind that the market returns are in fact the market excess returns as defined below. Additionally, we compute the excess returns for the pharmaceutical industry returns with our pharma index proxy and the excess returns of the average pharmaceutical and Big Pharma firm, respectively.

The **Market-Level Excess Returns** are calculated as the difference between the market index return and the risk-free rate of return at time t for monthly or yearly intervals s

$$R_{mts} = R_{MarketIndex,st} - R_{f_{st}}. \tag{7}$$

The **Pharmaceutical Industry-Level Excess Returns** are calculated as the return of the market plus an industry-specific residual series for each period t

$$R_{it} = R_{mt} + \epsilon_{it} \tag{8}$$

Lastly, the **Average Pharmaceutical Firm-Level Excess Returns** are calculated as the pharmaceutical industry return and a firm-level specific residual term for each period t and for our "big pharma variable", we calculate the weighted average return of the ten biggest biopharmaceutical firms over the average industry return (the Industry proxy we created, as seen in Equation 8).

$$R_{jit} = R_{it} + \eta_{jit} \tag{9.1}$$

$$R_{BPit} = R_{it} + \eta_{BPit} \tag{9.2}$$

From these excess return equations, we can therefore calculate the volatility measures

for our firm and industry variables (similar to how we calculate the volatility component for the MKT_t variable).

For the pharmaceutical industry we therefore have:

$$IND_t = \hat{\sigma}^2_{pharma,t} = \sum_{s \in t} \epsilon^2_{pharma,s} \tag{10}$$

By taking the similar approach of summing the squared residuals of the average firm-level excess return series, we thus have:

$$\hat{\sigma}^2_{\eta jit} = \hat{\sigma}^2_{\eta,j,pharma,t} = \sum_{s \in t} \eta^2_{j,pharma,s} \tag{11}$$

$$\hat{\sigma}^2_{\eta,j,pharma,t} = \sum_{j \in pharmaindustry} \omega_{jit} \hat{\sigma}^2_{\eta jit} \tag{12}$$

$$FIRM_t = \sum_i \omega_{pharma,t} \hat{\sigma}^2_{\eta pharma,t} \tag{13}$$

Our time intervals, as stated earlier, are monthly and yearly observations of volatility. With monthly and yearly series for the market, industry, big pharma and firm volatility estimates, we have eight volatility series for the period of 1990-2015. The following figures illustrate that firm-level (idiosyncratic) volatility is significantly higher than both industry-level and market-level volatility. Beyond our analysis of the average volatility of firm excess return, we delve deeper into this concept by isolating the variable we call "Big Pharma". Big Pharma is comprised of the ten firms with the highest market cap at the end of 2015. We treat these firms as separate from the rest of the 1,081 pharmaceutical and biotechnology firms because often they have different business models and capital structures than the smaller or more medium-sized biopharmaceutical firms. We keep the ten Big Pharma firms the same throughout the 1990-2015 year period. Just as the excess returns of the average firms are calculated, the excess returns of Big Pharma equal the Big Pharma gross returns less the Pharmaceutical Industry Index gross returns. Additionally, we eliminate the Big Pharma firms from the Pharma Index to control whether there is any significant impact on the results for our Industry variable (calculated from this Pharma

Industry Index we created), and we conclude that removing the Big Pharma firms does not have a significant effect on the numbers. We therefore do not include the variable of the Pharma Industry without the Big Pharma Firms for the rest of our calculations. Our calculation of the Big Pharma variable is shown in the equations below.

$$R_{BPit} = R_{it} + \eta_{BPit} \tag{14}$$

$$R_{BPts} = R_{BigPharma_{st}} - R_{PharmaIndex_{st}} \tag{15}$$

$$BP_t = \sum_i \omega_{BP_t} \hat{\sigma}^2_{\eta BP_t} \tag{16}$$

In total, we derive sixteen different volatility series, have a series for the Overall Market Returns, the Biopharmaceutical Industry Returns, the returns of an average Big Pharma firm, and the returns of an average biopharmaceutical firm. We have these series for monthly observations and yearly observations for each, and for both gross returns and excess returns. Each of the series are identified below.

16 Volatility Series

$MKT_{a,g}$	$BP_{a,g}$
$MKT_{a,e}$	$BP_{a,e}$
$MKT_{m,g}$	$BP_{m,g}$
$MKT_{m,e}$	$BP_{m,e}$
$IND_{a,g}$	$FIRM_{a,g}$
$IND_{a,e}$	$FIRM_{a,e}$
$IND_{m,g}$	$FIRM_{m,g}$
$IND_{m,e}$	$FIRM_{m,e}$

Table 1: Each volatility series evaluated in this analysis including for the market, the industry, the big pharma-level and the firm-level for annual and monthly gross and excess returns from 1990-2015

5.4 Data Summary Statistics

In the following tables, we show the summary statistics for the 16 series. Table 2 provides comprehensive summary statistics of the raw returns data, both for annual gross returns for each variable, and for annual excess returns for each variable. The returns have been annualized and are therefore expressed in yearly terms. What is noticeable initially, is that the variances of the Pharma Industry's returns (both gross and excess) are, as expected, higher than those of the market gross and excess returns. One may be able to infer then, that at the start the Pharmaceutical Industry seems slightly more volatile than the market. Table 3 shows the summary statistics for both the annual volatility series extracted from the gross and excess returns series for each variable, as well as the annualized volatility of the monthly series extracted from the monthly gross and excess returns series for each variable. What we see in this table is that the average pharma firm experiences the most idiosyncratic volatility, meaning that the variance measures at the firm level appear to be the highest. This observation is explained by diversification effects, and directly in line with Campbell et al. (2001) in that the firm experiences more idiosyncratic volatility than either the market or the industry. This observation holds for each of the firm-level series, and by firm-level in this instance, we are specifically referencing the variables of $FIRM_{a,g}$, $BF_{a,g}$, $FIRM_{a,e}$, $BF_{a,e}$, $FIRM_{m,g}$, $BF_{m,g}$, $FIRM_{m,e}$, and $BF_{m,e}$.

With regard to the other summary statistics, it appears that the raw gross returns for each series are negatively skewed, meaning that the left tail of the distribution is larger than the right tail. This negative skewness persists with the excess raw returns only for the market, however. Every other series then adopts a positive skewness, meaning that the excess returns at the industry, firm, and big pharma level have larger right-side tails. Furthermore, positive skewness is completely present in all series in the volatility series summary statistics table, again, implying that the right-side tail is thicker. Regarding kurtosis, one can see from the tables that both kurtosis and excess kurtosis are not astoundingly high for the raw returns series. The excess kurtosis is very high, however, for the volatility series at the monthly level. These large measures of kurtosis imply that more of the variance is actually due to infrequent but very large deviations from the mean as opposed to much more frequent but much smaller deviations in the series.

Table 8 shows the autocorrelation structure for our eight volatility series. It is clear that the series are, in fact, autocorrelated, and that autocorrelation is still present for the annual volatility series even with a lag of five years. Autocorrelation is also present, however, in the monthly series, and still at a significant level after a lag of eighteen months. One could conclude therefore, that there must be some type of persistence in the trend of the volatities of both the gross and excess returns series.

Annualized Yearly Raw Returns Series: Gross and Excess

	Mean	Variance	Skewness	Kurtosis	Excess Kurtosis	Minimum	Maximum
MKT_{gross}	0.0395	0.0283	-0.5895	3.5332	0.5332	-0.4151	0.3302
IND_{gross}	0.0557	0.0454	-0.6187	2.8577	-0.1423	-0.4611	0.3649
$FIRM_{gross}$	-0.0199	0.0130	-0.7296	4.0719	1.0719	-0.3151	0.1862
BF_{gross}	0.0034	0.0015	-0.1922	2.1981	-0.8019	-0.0702	0.0670
MKT_{excess}	0.0192	0.0294	-0.5049	3.3355	0.3355	-0.4246	0.3292
IND_{excess}	0.0162	0.0382	0.0456	4.1809	1.1809	-0.4349	0.5374
$FIRM_{excess}$	-0.0756	0.0349	1.2206	4.3711	1.3711	-0.3391	0.4133
BP_{excess}	-0.0523	0.0374	0.7072	3.1964	0.1964	-0.3422	0.4539

Table 2: Summary Statistics of the Annual Raw Returns Series (expressed in terms of annualized return percentages) for the raw gross and raw excess returns series for the market, pharmaceutical industry, the average pharmaceutical firm, and big pharma firms from 1990-2015.

Summary Statistics for Each Volatility Series of Gross and Excess Returns (Annual and Monthly)

Annual Volatility Series	Mean	Variance	Skewness	Kurtosis	Excess Kurtosis	Minimum	Maximum
$MKT_{ann,gross}$	0.1646	0.0057	1.4132	5.1482	2.1482	0.0748	0.4067
$IND_{ann,gross}$	0.1965	0.0041	0.3905	1.9450	-1.0550	0.1089	0.3142
$FIRM_{ann,gross}$	0.7908	0.0167	0.7974	2.9656	-0.0344	0.6106	1.0880
$BF_{ann,gross}$	0.3424	0.0174	0.6841	2.4294	-0.5706	0.1909	0.6469
$MKT_{ann,excess}$	0.1646	0.0057	1.4131	5.1477	2.1477	0.0748	0.4067
$IND_{ann,excess}$	0.1379	0.0032	0.8187	2.5821	-0.4179	0.0704	0.2642
$FIRM_{ann,excess}$	0.7811	0.0163	0.6298	2.6311	-0.3689	0.5980	1.0716
$BF_{ann,excess}$	0.2845	0.0180	0.9180	2.9193	-0.0807	0.1353	0.6221
Monthly Volatility Series	Mean	Variance	Skewness	Kurtosis	Excess Kurtosis	Minimum	Maximum
$MKT_{mon,gross}$	0.1553	0.0088	2.8034	15.1564	12.1564	0.0449	0.7960
$IND_{mon,gross}$	0.1846	0.0090	2.2033	10.9924	7.9924	0.0575	0.8090
$FIRM_{mon,gross}$	0.7000	0.0272	1.7036	7.2736	4.2736	0.4507	1.4886
$BF_{mon,gross}$	0.2535	0.0215	2.3677	12.4691	9.4691	0.0399	1.1488
$MKT_{mon,excess}$	0.1553	0.0088	2.8034	15.1564	12.1564	0.0449	0.7960
$IND_{mon,excess}$	0.1282	0.0060	2.4536	14.1926	11.1926	0.0392	0.7198
$FIRM_{mon,excess}$	0.6905	0.0261	1.3494	5.4838	2.4838	0.4505	1.3793
$BF_{mon,excess}$	0.2039	0.0174	3.1355	19.4657	16.4657	0.0560	1.2113

Table 3: Summary Statistics for all Volatility Series (1990-2015)

Volatility Series Correlation Matrix 1

	$FIRM_{a,e}$	$BP_{a,e}$	$IND_{a,e}$
$BP_{a,e}$	0.4702		
$IND_{a,e}$	0.7555	0.6440	
$MKT_{a,e}$	0.6522	-0.0974	0.3617

Table 4: Cross Correlations between the Annual Excess Returns Volatility Series for the Market, the Pharma Industry, Big Pharma, and the Average Pharma firm between 1990 and 2015

Volatility Series Correlation Matrix 2

	$FIRM_{a,g}$	$BP_{a,g}$	$IND_{a,g}$
$BP_{a,g}$	0.5096		
$IND_{a,g}$	0.6715	0.6445	
$MKT_{a,g}$	0.7326	0.1260	0.5615

Table 5: Cross Correlations between the Yearly Gross Returns Volatility Series for the Market, the Pharma Industry, Big Pharma, and the Average Pharma firm between 1990 and 2015

Volatility Series Correlation Matrix 3

	$FIRM_{m,e}$	$BP_{m,e}$	$IND_{m,e}$
$BP_{m,e}$	0.4639		
$IND_{m,e}$	0.6657	0.4933	
$MKT_{m,e}$	0.6207	0.1194	0.4059

Table 6: Cross Correlations between the Monthly Excess Returns Volatility Series for the Market, the Pharma Industry, Big Pharma, and the Average Pharma firm between 1990 and 2015

Volatility Series Correlation Matrix 4

	$FIRM_{m,g}$	$BP_{m,g}$	$IND_{m,g}$
$BP_{m,g}$	0.5378		
$IND_{m,g}$	0.6299	0.5367	
$MKT_{m,g}$	0.7147	0.3479	0.6217

Table 7: Cross Correlations between the Monthly Gross Returns Volatility Series for the Market, the Pharma Industry, Big Pharma, and the Average Pharma firm between 1990 and 2015

Autocorrelation Structure of Each Volatility Series (Annual and Monthly)

Annual Lag	MKT_{gross}	IND_{gross}	$FIRM_{gross}$	BF_{gross}	MKT_{excess}	IND_{excess}	$FIRM_{excess}$	BF_{excess}
ρ_1	0.8976	0.9126	0.9494	0.9383	0.8976	0.9189	0.9516	0.9439
ρ_2	0.8199	0.8511	0.9036	0.9029	0.8199	0.8348	0.9063	0.9099
ρ_3	0.7753	0.7972	0.8663	0.8780	0.7753	0.7760	0.8678	0.8715
ρ_4	0.7163	0.7561	0.8305	0.8214	0.7163	0.7376	0.8318	0.8183
ρ_5	0.6772	0.7364	0.7968	0.7764	0.6772	0.7118	0.7986	0.7573
Monthly Lag	MKT_{gross}	IND_{gross}	$FIRM_{gross}$	BF_{gross}	MKT_{excess}	IND_{excess}	$FIRM_{excess}$	BF_{excess}
ρ_1	0.9288	0.9013	0.9889	0.9288	0.8721	0.9898	0.8392	0.7947
ρ_2	0.8879	0.8624	0.9801	0.8879	0.8337	0.9818	0.8375	0.7998
ρ_3	0.8626	0.8514	0.9721	0.8626	0.8391	0.9750	0.8040	0.7772
ρ_4	0.8340	0.8341	0.9638	0.8340	0.8216	0.9683	0.8158	0.8110
ρ_6	0.8148	0.8173	0.9532	0.8148	0.8109	0.9587	0.8227	0.8228
ρ_{12}	0.7764	0.7956	0.9266	0.7764	0.7887	0.9318	0.7956	0.7762
ρ_{18}	0.7547	0.7712	0.9056	0.7547	0.7384	0.9103	0.7703	0.7586

Table 8: Autocorrelation Structures of Each Volatility Series (1990-2015)

In order to determine whether or not our volatility series had a Unit-Root, we perform two different Augmented Dickey-Fuller tests on each of the eight series. The first ADF test includes a linear time trend as well as a coefficient, where the second test excludes the linear time trend and only contains a coefficient. In line with Campbell et al. (2001), we find that each of the volatility series, if differenced, do not contain a unit root. Often it is common for financial or economic time series to have some type of unit-root or at least have integration at the first level, but by taking the ADF statistic of the differenced volatility series, the unit root null hypothesis (that we would be unable to reject the possibility of the presence of a unit root in each series) was rejected. This means that since our ADF statistics for each of the volatility series in both of the different tests (with the linear time trend and without the linear time trend) are more negative than the ADF critical values as determined by the Augmented Dickey-Fuller test, we are able to reject the null hypothesis and conclude that the differenced series did not contain a unit root. We would have expected to find some type of unit root at least in the first order of integration, not only given that this is a volatility time series based off of a financial time series, but also because of the autocorrelation presence in the volatility series itself. Because there is some

ADF Results with a Linear Time Trend and a Coefficient

ADF Critical Value: -4.1831		
Annual Volatility Series	ADF Stat	p-value
$MKT_{ann,gross}$	-5.1370	0.0113
$IND_{mon,gross}$	-5.4630	0.0074
$FIRM_{mon,gross}$	-4.6318	0.0228
$BF_{ann,gross}$	-6.4192	0.0028
$MKT_{ann,excess}$	-5.1368	0.0113
$IND_{ann,excess}$	-5.3737	0.0108
$FIRM_{ann,excess}$	-4.3256	0.0351
$BF_{ann,excess}$	-6.1878	0.0035
ADF Critical Value: -3.4398		
Monthly Volatility Series	ADF Stat	p-value
$MKT_{mon,gross}$	-5.1818	0.0000
$IND_{mon,gross}$	-9.7563	0.0000
$FIRM_{mon,gross}$	-11.1455	0.0000
$BF_{mon,gross}$	-9.0046	0.0000
$MKT_{mon,excess}$	-5.1818	0.0000
$IND_{mon,excess}$	-10.0571	0.0000
$FIRM_{mon,excess}$	-11.2647	0.0000
$BF_{mon,excess}$	-13.0107	0.0000

Table 9: ADF Results for all Volatility Series (1990-2015), showing that at the five percent confidence level, we are able to reject the null hypothesis that there is a possibility that all of our series are non-stationary and have a unit-root presence.

ADF Results without a Linear Time Trend

ADF Critical Value: -3.3702		
Annual Volatility Series	ADF Stat	p-value
$MKT_{ann,gross}$	-5.0334	0.0042
$IND_{ann,gross}$	-5.3696	0.0029
$FIRM_{ann,gross}$	-4.5593	0.0080
$BF_{ann,excess}$	-6.2493	0.0000
$MKT_{ann,excess}$	-5.0332	0.0042
$IND_{ann,excess}$	-5.1738	0.0043
$FIRM_{ann,excess}$	-4.2584	0.0128
$IBF_{ann,excess}$	-5.9544	0.0000
ADF Critical Value: -2.9007		
Monthly Volatility Series	ADF Stat	p-value
$MKT_{mon,gross}$	-4.8733	0.0000
$IND_{mon,gross}$	-9.5194	0.0000
$FIRM_{mon,gross}$	-11.0201	0.0000
$BF_{mon,gross}$	-8.7243	0.0000
$MKT_{mon,excess}$	-4.8732	0.0000
$IND_{mon,excess}$	-9.8102	0.0000
$FIRM_{mon,excess}$	-11.1383	0.0000
$BF_{mon,excess}$	-12.7798	0.0000

Table 10: ADF Results for all Volatility Series (1990-2015), without a linear time trend, showing that at the five percent confidence level, we are able to reject the null hypothesis that there is a possibility that all of our series are non-stationary and have a unit-root presence.

significant autocorrelation in the observations of each of the volatility series (the original, non-differenced series, both monthly and annual), it would be expected that there might exist some form of unit root integrated at the lower levels.

According to the methodology of Campbell et al. (2001), after testing the difference of the volatility series for the presence of a unit root, the next test to perform would be a test to see if there exists any prevailing linear trend in the volatility series. This would entail testing to see whether or not there is a trend in the series that would imply that the overall levels of volatility in the market, the industry, or at the average firm level have increased over time. There is significant noice from the recessions in our timeframe but from looking at the volatility data however, and as can be seen in the following graphs showing the volatility evolution over time, it does not appear that there is an increasing linear trend in any of the volatility series. Perhaps in the last five to seven years of data there appears to be some type of level increase in firm-level volatilities, but other than that, there is no perceivable "structural break" of significance appearing in our data. This means that (in accordance with our unit root of the differenced volatility series findings and our autocorrelation findings) there is some type of standard level of volatility that the values in each series fluctuate around. This is standard for the market, and although we initially expected that the volatility levels within the biopharmaceutical industry and firm-levels are higher than in the average market level for excess and gross returns we had not made any direct hypothesis about the behavior of such volatility trends over time. It is true that there are higher levels of volatility in the industry and in the firm-level than in the market, however, over time it does not appear that (even though this difference persists) that any individual series experiences a structural break and the mean level of volatility reaches an entirely new level and there is a new mean to which the volatility would then revert.

Worth mentioning here is also the degree of cross-correlations between the various volatility series. It appears that the correlation between the biopharmaceutical industry and the actual market is relatively low, especially for the excess returns volatility series at the annual and monthly frequencies. The highest value here is roughly 0.41, meaning that the majority of the deviations in the pharmaceutical industry series are not in fact due to

the industry's mirroring of apparent market fluctuations. Furthermore, our Big Pharma series seem to have the lowest correlation with any of the other series, which would have been expected, due to the capital structure and the scale of the large pharmaceutical firms being very different from that of an average firm being traded on the market. Just as there are moments in the volatility series that Big Pharma remain more stable than the biopharmaceutical industry on average, one can see in the cross-correlation matrices that Big Pharma's returns are weakly correlated with the fluctuations of the market volatility series, although they are more correlated with the industry volatility series. The firm level volatility series seem to be strongly correlated with both the industry and the market series in all cases, showing that although there is a significant difference in the level of volatility between the firm and the market or the firm and the industry, many of the movements in the firm volatility series are similar to those of the industry and the market. With these cross-correlations however, especially of the monthly excess returns volatilities having a correlation between the market and the industry of roughly only 0.41 and the yearly volatility series with a correlation between those two of only 0.36, we hope to see whether or not there are industry-specific characteristics that can help to explain the fluctuations in volatility and the behavior of the series that can be observed over time in our data.

In the following sections, we will discuss the results of our volatility decomposition analysis and attempt to explain our results and discern whether or not they can be explained with a factor model regression based off of industry-specific characteristics.

6 Results

The initial empirical methodology involves a beta-free variance decomposition. This means that we seek to determine the differences in volatility levels between the gross and excess returns of the market, the biopharmaceutical industry, the average big pharma firm and the average pharma firm. Essentially, the variance decompositions involves computing the annualized returns and excess returns as a form of a weighted average between all of the firms listed in the market, our industry proxy, our big pharma proxy, and an average of

all the biopharmaceutical firms in our sample, obtaining their standard deviations and variances. The following figures illustrate the results of our efforts in the form of four separate line graphs. Figure 1 illustrates the annual volatility for the annualized gross returns of each of our four series ($MKT, IND, BP, FIRM$), while Figure 2 provides the same information but for the annualized excess returns of each series. Figures 3 and 4 provide the information similar to the previously mentioned tables but at the monthly level for annualized gross and excess returns.

What is evident from these graphs is that our initial hypothesis seems to be valid. There is a higher level of volatility (for the vast majority of observations) at the big pharma and average firm level. There is more volatility at the pharma & biotech industry level than there is at the market level. This means that there is increased idiosyncratic risk at the industry and firm levels for pharma and biotech, which is a clear diversification effect and is to be expected. The second aspect of interest here is that it is unclear whether or not there exists any type of structural break or linear trend of an increase in volatility for each individual series. This being said, although there is autocorrelation between the observations of the volatility series, the overall mean volatility over time does not seem to increase for any of the series being analyzed. Although we would not have expected any such structural break in the volatility series for the market, it would not have been unreasonable to expect some type of steady increase throughout time in the volatility at the pharma industry level or firm levels, given that in the next section it is our intention to help explain the behavior of such volatility for pharma firms with the increased M&A activity permeating the business environment of the biopharmaceutical industry in recent years. Within the last five years or so however, there does appear to be some steady increase in the firm-level volatility, yet the increase is not prolonged enough to draw any significant inferences about any potential long-term trending behavior of the volatility. If this increase in volatility persists, however, one could perhaps in the future be able to associate it with the significant increase in number of merger and acquisition deals executed within the industry during this time period (these results can be seen in Figures 5 and 7).

Regarding the figures of our volatility series, we see also that larger macroeconomic

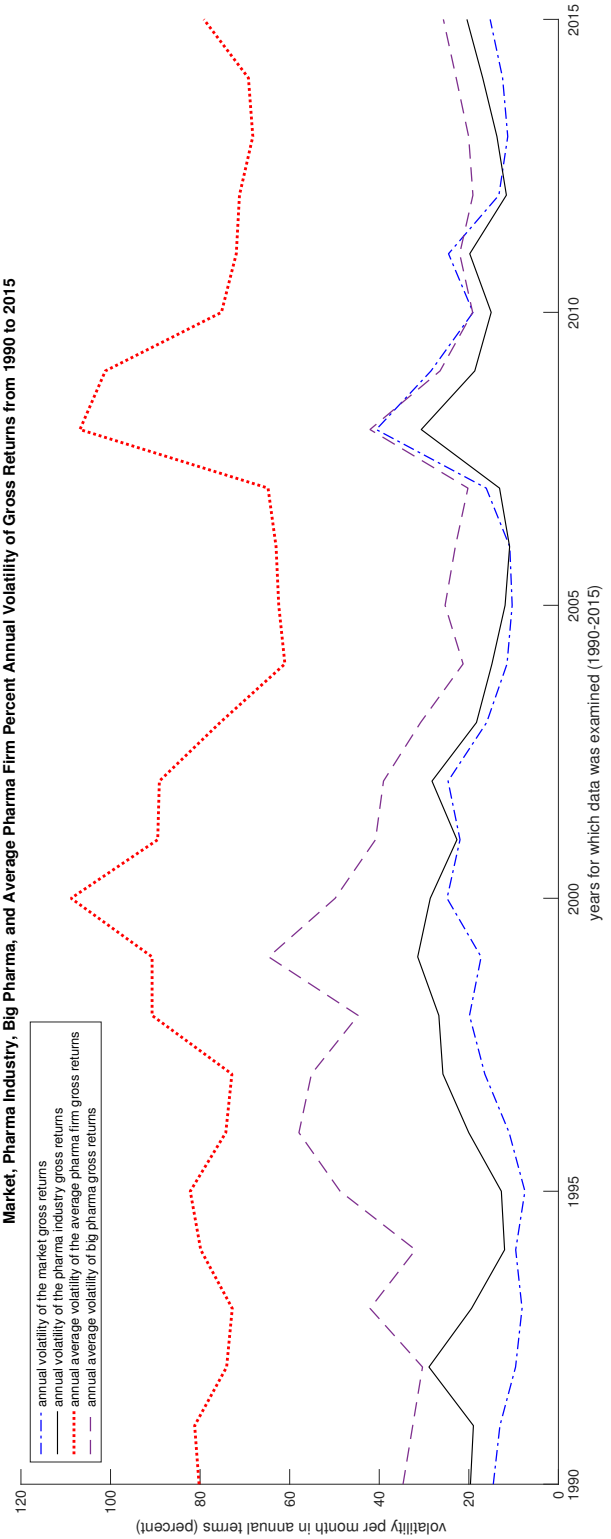

Figure 1: Annual Volatility for the Market-, Industry-, Average Big Pharma-, and Average Pharmaceutical Firm-Level Gross Returns from 1990-2015

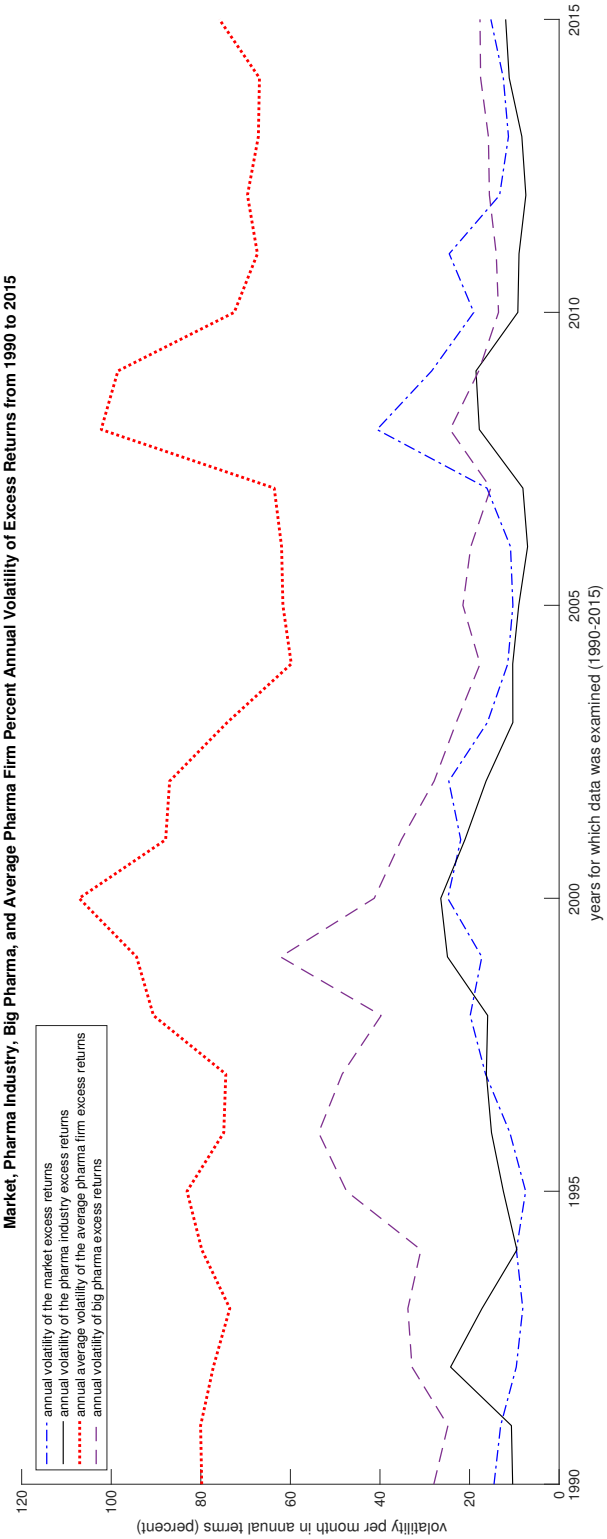

Figure 2: Annual Volatility for the Market-, Industry-, Average Big Pharma-, and Average Pharmaceutical Firm-Level Excess Returns from 1990-2015

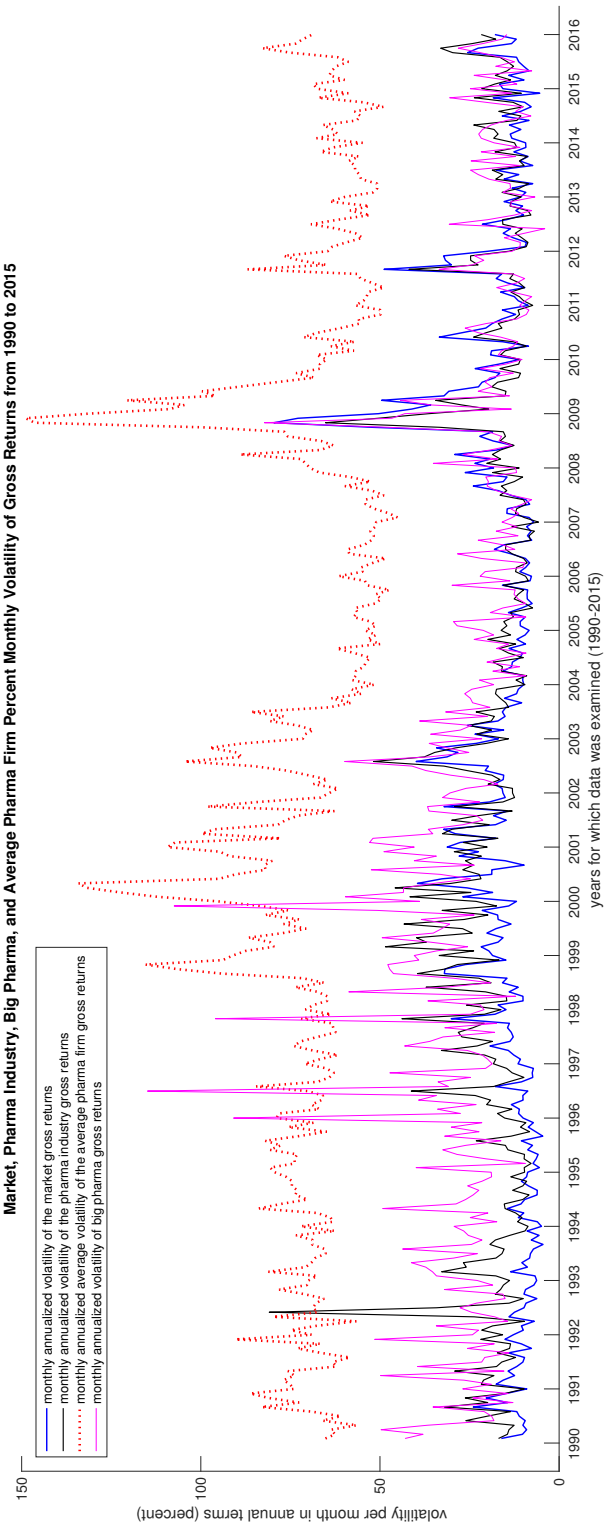

Figure 3: Monthly Volatility in Annual terms for the Market-, Industry-, Average Big Pharma-, and Average Pharmaceutical Firm-Level Gross Returns from 1990-2015

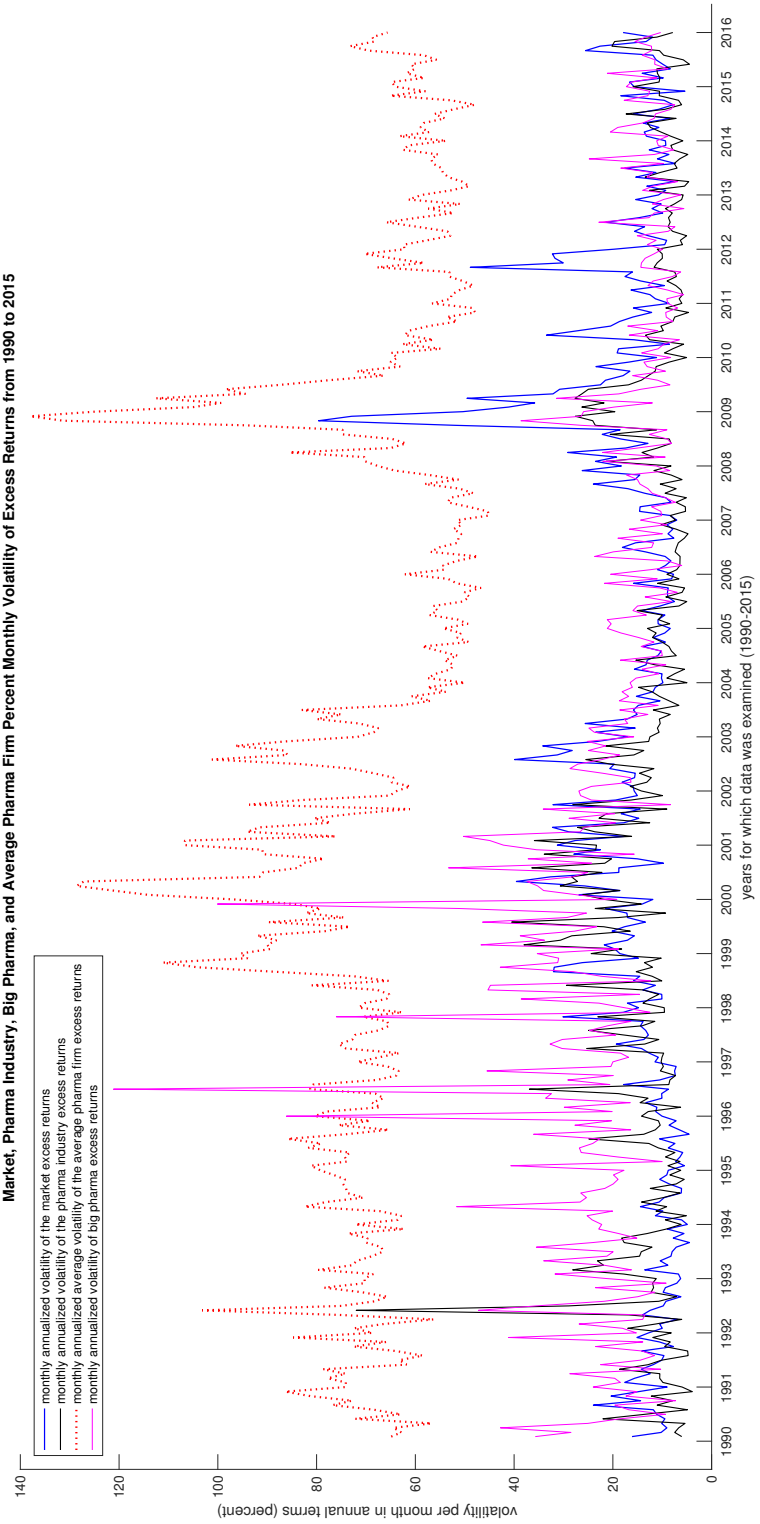

Figure 4: Monthly Volatility in Annual terms for the Market-, Industry-, Average Big Pharma-, and Average Pharmaceutical Firm-Level Excess Returns from 1990-2015

events do in fact affect the market to a significant extent and also specifically impact the industry and firm levels. This could be due to the fact that business operations in recession years become more difficult overall: funding is more difficult to obtain for any type of expansion or growth projects, and the economy slows down to a point where consumer uncertainty takes hold and is reflected in market returns until the economy recovers. Additionally, as we stated in the industry overview section, the volatility levels at the industry and pharma firm levels are heavily affected by any regulatory action. The pharmaceutical industry is heavily regulated due to the direct impact pharmaceutical products and medical innovations can have on the lives of consumers. With this in mind, it is clear that the industry itself is very sensitive to the passage of any intense new regulations. Again another industry characteristic is the propensity for the industry to consolidate (something we examine further in the next section). As there seems to be M&A deals constantly happening within the industry, there is sure to be uncertainty surrounding any acquisitions in the market because the business environment is rapidly changing. There could exist pressures for firms to undertake acquisition efforts or merge with other large firms, and they may end up paying a large (and unnecessary) premium for a deal that may not ultimately benefit the firm. With this changing business environment, there could be higher volatility at the firm level overall as the firms navigate how to maintain their product pipelines and successfully operate their corporations in this new and more challenging environment.

It is worth noting that we do make a conscious effort to differentiate between what is termed the big pharma firms and the average pharma firm. The reason we do this is mostly due to the sheer size of the biggest biopharmaceutical firms and the difference in their operations. As Danzon et al. (2004) notes, by the early 2000's, only the ten or so largest pharma corporations accounted for roughly half of the pharma industry revenue within the United States. Keeping this statistic in mind, it would then make sense that these firms could potentially have cash buffers and different capital structures, because at the end of the day these large corporations are accountable to their shareholders who expect returns on their investments in the form of shareholder friendly behavior on behalf of the corporation. So, even as these larger firms focus their efforts more on global

marketing scale and scope, and acquire more patents and exclusivity rights to products they came to own through outright acquisition rather than in-house research efforts, they still must ensure their product pipelines in such a way that they can provide anticipated financial returns to their investors. As can be clearly seen in Figure 2, the volatility of the average pharma firm is quite high, even for industry standards. However, what is more interesting to note, is that the volatility of the pharma industry (as derived from our Pharma Index Proxy of all 1091 firms traded on the NYSE and AMX), is actually higher than the volatility of the excess returns of the big pharma firms during the same time period. This increased volatility could surely be largely attributed to the financial crisis and the recession that greatly affected the United States economy, but one can see that it is quite intriguing that the big pharma firms did not have that same level of increased uncertainty as the rest of the firms in its industry or its industry overall. Although it is not the intention of our efforts in this paper to be able to explain why the big pharma firms were able to bypass major increases in volatility levels of excess returns, it could lead one to infer that these firms did in fact have some type of buffer to be able to still deliver returns as expected to their shareholders in a way that was not entirely different from the returns shareholders could have expected outside of the recession.

7 An Additional Step in Empirical Analysis: What Might Explain Increasing Idiosyncratic Volatility?

7.1 Potential Explanatory Regressions Involving M&A Activity Data

In order to examine one potential explanation of increasing volatility, we analyse statistics for M&A transactions executed in the timeframe for our data (1990-2015). Using data obtained from Bloomberg we aggregate the number of deals and total deal value within the pharma & biotech industry per year and per month for our entire time frame.

M&A activity in general is thought not to be as gravely affected by recessions as other parts of the economy, since many companies seek to restructure in uncertain times. For the general M&A market, this usually manifests itself through a decrease in deals after the recession has essentially played out, but before the market picks up speed. In our

data on M&A in the pharma and biotech industry, we see a decline in deal numbers in the early 00's, after the IT bubble, but also a slowdown in the number of deals trailing the financial crisis before a large increase in 2014 and 2015. In terms of total deal value, the impact of recessions and crises is much more notable. This metric is largely influenced by a few extremely large mega-deals, which are in turn unlikely to happen in uncertain times. As such, we note in our data a large decline in 2000, 2003, 2009 and 2012-2013. It is reasonable to think that the possibility for companies to pursue these very large deals is limited during crises due to unstable markets, financing constraints, and a risk aversion that includes a reluctance to pay any sort of extreme premium for acquisitions.

During the time period, we can see a clear trend consisting of an increased number of deals as well as an increase in total deal value. The number of deals per year has increased steadily since 1990 with only a few years presenting a decline in the number of deals. Apart from a real increase in the number of deals, we also have reason to believe that Bloomberg, from where we collect our data, has less extensive deal data for the first few years as compared to more recent years.

Looking at monthly data, the number of deals as well as the deal value varies largely between months. This is somewhat due to chance - if a deal is announced the last day of one month or the first day of the next, but also due to some seasonal variation. However, using monthly data gives us a larger number of observations, and a better way to examine the relationship between volatility and deal activity since both variables can experience extensive variation within any given period.

7.2 M&A Activity in relation to volatility

In order to examine the relationship between M&A activity and volatility we start by calculating basic correlations. We find the correlation between the number of deals per month and average firm-level excess return to be -0.34, or -0.39 if we only examine the period 2000-2015, where there are more deals per month. For the gross return volatilities, corresponding correlation numbers are -0.24 and -0.35 for the full time period and the 2000-2015 sample respectively. Correlations between total deal value per month and

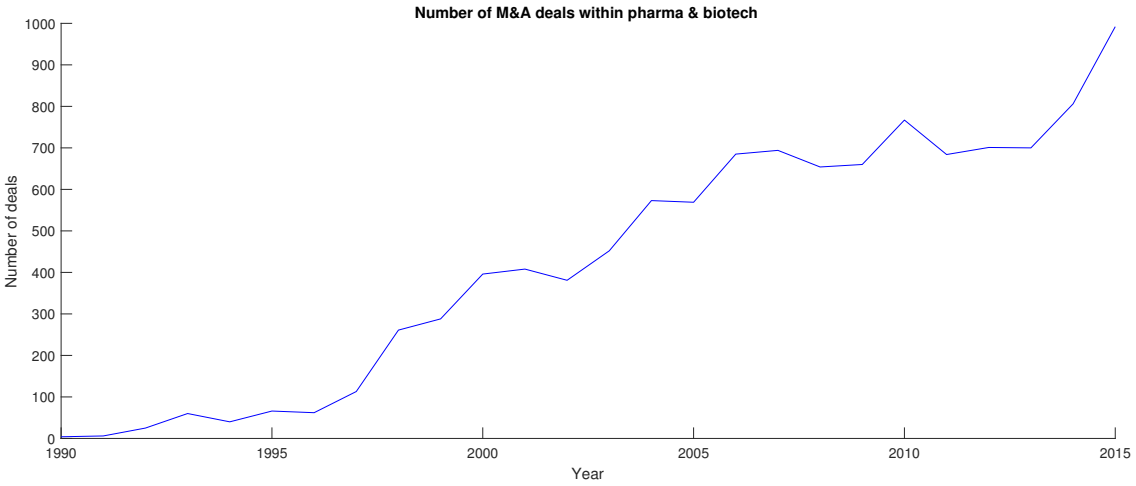

Figure 5: Number of M&A deals yearly from 1990-2015

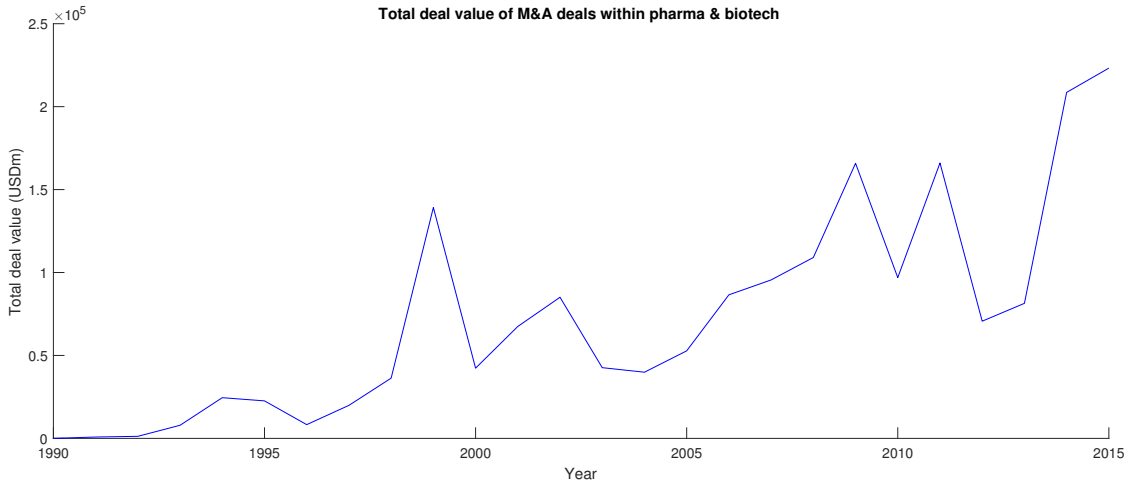

Figure 6: Total deal value of M&A deals yearly from 1990-2015

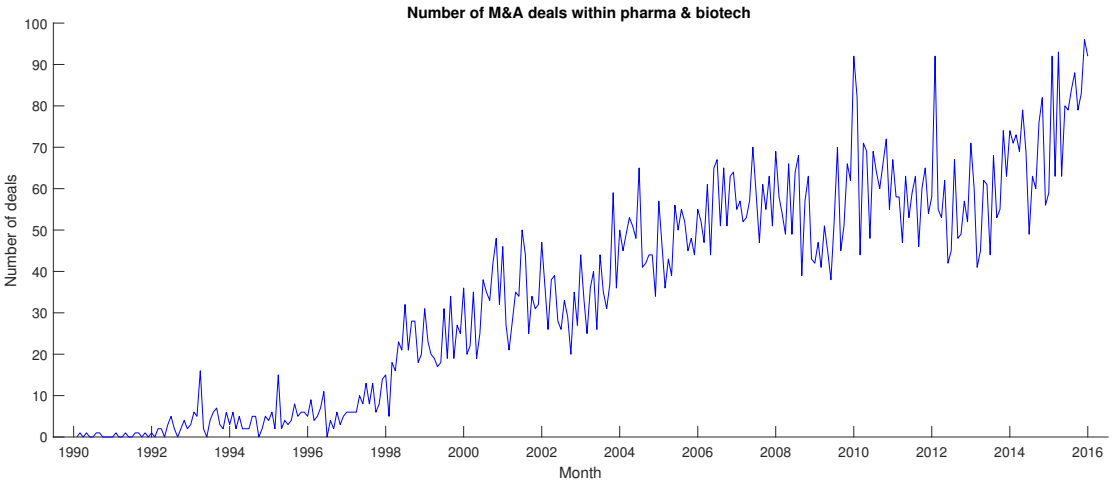

Figure 7: Number of M&A deals monthly from 1990-2015

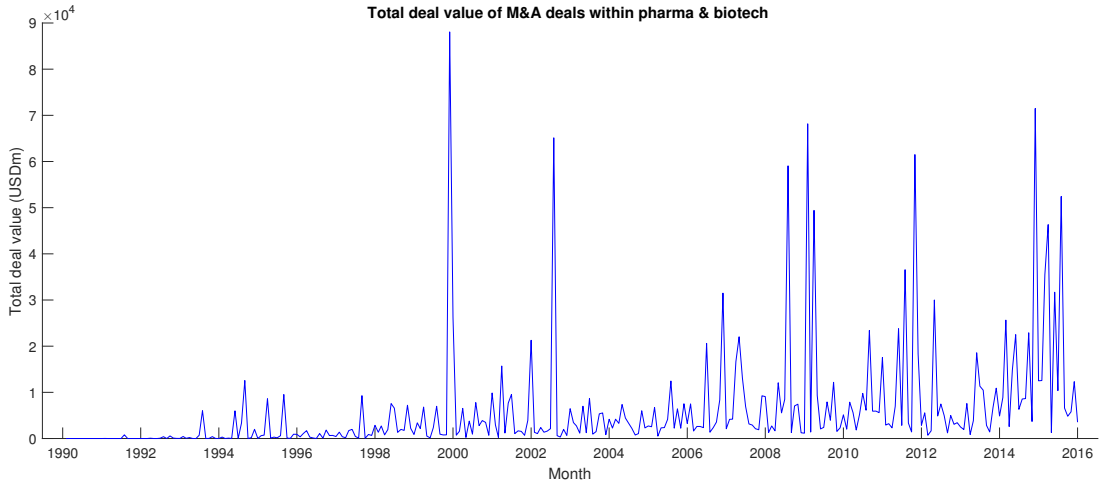

Figure 8: Total deal value of M&A deals monthly from 1990-2015

volatility turn out to be very close to zero for all volatility series (ranging between -0.003 and 0.090.

Below are the four different regressions we performed on our firm-level volatility series for both the excess and the gross returns of the monthly and yearly series:

$$FIRM_{a,e} = \alpha_{1_t} + \beta_{1_t} DealNUM_{yrly_t} + \beta_{2_t} DealVAL_{yrly_t} + \epsilon_{1_t} \tag{17}$$

$$FIRM_{a,e} = \alpha_{2_t} + \beta_{1_t} DealNUM_{yrly_t} + \beta_{2_t} DealVAL_{yrly_t} + \beta_{3_t} RecYr_t + \epsilon_{2_t} \tag{18}$$

$$FIRM_{a,g} = \alpha_{3_t} + \beta_{1_t} DealNUM_{yrly_t} + \beta_{2_t} DealVAL_{yrly_t} + \epsilon_{3_t} \tag{19}$$

$$FIRM_{a,g} = \alpha_{4_t} + \beta_{1_t} DealNUM_{yrly_t} + \beta_{2_t} DealVAL_{yrly_t} + \beta_{3_t} RecYr_t + \epsilon_{4_t} \tag{20}$$

$$FIRM_{m,e} = \alpha_{5_t} + \beta_{1_t} DealNUM_{mthly_t} + \beta_{2_t} DealVAL_{mthly_t} + \epsilon_{5_t} \tag{21}$$

$$FIRM_{m,e} = \alpha_{6_t} + \beta_{1_t} DealNUM_{mthly_t} + \beta_{2_t} DealVAL_{mthly_t} + \beta_{3_t} RecYr_t + \epsilon_{6_t} \tag{22}$$

$$FIRM_{m,g} = \alpha_{7_t} + \beta_{1_t} DealNUM_{mthly_t} + \beta_{2_t} DealVAL_{mthly_t} + \epsilon_{7_t} \tag{23}$$

$$FIRM_{m,g} = \alpha_{8_t} + \beta_{1_t} DealNUM_{mthly_t} + \beta_{2,t} DealVAL_{mthly_t} + \beta_{3_t} RecYr_t + \epsilon_{8_t} \tag{24}$$

M&A Activity and Volatility Series Cross-Correlation Results

			$FIRM_{a,e}$	$FIRM_{a,g}$
Yearly	1990-2015	$DealNUM$	-0.246	-0.138
		$DealVAL$	0.008	0.090
	2000-2015	$DealNUM$	-0.381	-0.344
		$DealVAL$	0.011	0.057
			$FIRM_{m,e}$	$FIRM_{m,g}$
Monthly	1990-2015	$DealNUM$	-0.337	-0.242
		$DealVAL$	-0.003	0.035
	2000-2015	$DealNUM$	-0.389	-0.353
		$DealVAL$	0.032	0.047

Table 11: Correlation between the average biopharmaceutical firm excess and gross annual and monthly returns and the annual and monthly M&A deal count and deal value data between the years of 1990-2015

In order to see if the increased deal activity in later years has had an impact on firm volatility, we perform different regressions of our volatility series on the deal data. Since it is known that volatility spikes in recessions, we include a dummy variable taking the value of 1 for NBER-dated recessions, and 0 otherwise. The results are found in Tables 12 and 13 below.

To increase the detail in our observation, and since volatility can vary significantly within a given year, we repeat the same regressions for our monthly sample. We note that our coefficients are more significant, but that more or less the results from the yearly data hold. A one standard deviation increase in the number of deals leads to a decrease in excess return volatility for the average firm of 6.3%, and a one standard deviation increase in total deal value corresponds to a 2.3% increase in volatility. Recessions are strongly significant.

Regressing on yearly volatility data, we find that the number of deals per year has a significant impact on firm excess return volatility, an effect that remains when recessions are controlled for. The coefficient of -0.0003 suggests that essentially, a one standard deviation increase in deal number decreases the volatility of excess returns of the average pharma & biotech firm by 9.3%. The yearly deal value is significant when recessions are not controlled for, albeit only at the 90% level, and drops just below the threshold of

Table 12: Regression results for Annual Firm Level Excess and Gross Volatility Series on Mergers and Acquisitions Data from 1990-2015

	Dependent variable:			
	$FIRM_{y,e}$		$FIRM_{y,g}$	
	(1)	(2)	(3)	(4)
$DealNUM_{yearly}$	-0.0003^{**}	-0.0003^{**}	-0.0003^{*}	-0.0002^{*}
	(0.0001)	(0.0001)	(0.0001)	(0.0001)
$DealVAL_{yearly}$	$1.175x10^{-6*}$	$9.773x10^{-7*}$	$1.158x10^{-6*}$	$9.397x10^{-7*}$
	(0.00000)	(0.00000)	(0.00000)	(0.00000)
$RecYr$		0.153^{**}		0.169^{**}
		(0.059)		(0.060)
Constant (α)	0.824^{***}	0.802^{***}	0.815^{***}	0.790^{***}
	(0.041)	(0.038)	(0.043)	(0.039)
Observations	26	26	26	26
R^2	0.182	0.372	0.134	0.361
Adjusted R^2	0.111	0.287	0.059	0.274
Residual Std. Error	0.120 (df = 23)	0.108 (df = 22)	0.125 (df = 23)	0.110 (df = 22)
F Statistic	2.559^{*} (df = 2; 23)	4.349^{**} (df = 3; 22)	1.779 (df = 2; 23)	4.138^{**} (df = 3; 22)
Note:				*p<0.1; **p<0.05; ***p<0.01

Table 13: Regression results for Monthly Firm Level Excess and Gross Volatility Series on Mergers and Acquisitions Data from 1990-2015

	Dependent variable:			
	$FIRM_{m,e}$		$FIRM_{m,g}$	
	(1)	(2)	(3)	(4)
$DealNUM_{monthly}$	-0.002^{***}	-0.002^{***}	-0.002^{***}	-0.002^{***}
	(0.0004)	(0.0003)	(0.0004)	(0.0003)
$DealVAL_{monthly}$	$1.951x10^{-6**}$	$1.654x10^{-6**}$	$2.035x10^{-6**}$	$1.705x10^{-6**}$
	(0.00000)	(0.00000)	(0.00000)	(0.00000)
$RecYr$		0.167^{***}		0.186^{***}
		(0.024)		(0.025)
Constant (α)	0.764^{***}	0.744^{***}	0.754^{***}	0.732^{***}
	(0.014)	(0.014)	(0.015)	(0.014)
Observations	312	312	312	312
R^2	0.131	0.246	0.077	0.213
Adjusted R^2	0.125	0.239	0.071	0.205
Residual Std. Error	0.151 (df = 309)	0.141 (df = 308)	0.159 (df = 309)	0.147 (df = 308)
F Statistic	23.311^{***} (df = 2; 309)	33.503^{***} (df = 3; 308)	12.820^{***} (df = 2; 309)	27.724^{***} (df = 3; 308)
Note:				*p<0.1; **p<0.05; ***p<0.01

significance when recessions are controlled for. The coefficient suggests that a one standard deviation increase in total deal value increases volatility by 7.5%. It is worth noting that recessions do have a significant impact on the volatility measure.

Regressing on the gross return volatilities of the average pharma & biotech firm, we find that the relationships between the variables are very similar, though less significant. The coefficients also have roughly the same magnitude.

Our results are largely consistent with Bharath and Wu (2005) in that we would expect mergers to be executed at or closely before spikes in volatility. The merger would then have a stabilising effect on the average firm, in line with theories about M&A activities as response to industry shocks. It is reasonable to expect then that M&A activity could then be stabilising force, and as such the negative coefficient on the deal number variable in our regressions is explained. Furthermore, along the same line of thought as Higgins and Rodriguez (2006), the firms that are engaging in these mergers or acquisitions may truly be using them to realize the positive returns of a successful merger, meaning that those activities are actually the best options for the firms in the market at the time. The smaller biopharma firms could be using the M&A transactions as a type of exit strategy, while the larger firms may successfully be using these transactions to sure up their product pipelines and guarantee future returns to their shareholders. Thus, this M&A activity could act as a stabilizing force within the market, helping to alleviate possible future volatility from unstable companies or firms that are better off being acquiring or partnering with other firms in the industry. Another aspect to consider here is that the professionals involved in the business side of the biopharmaceuticals industry often need to be very familiar with the operations of the industry in order to be successful. This means that not only must they be well-versed in the financial side of such transactions, being able to evaluate potential deals, but they must also be able to understand the sophisticated nuances that are specific to the environment of the biopharmaceutical industry. Being able to understand both aspects would then mean that these companies truly understand the nature of the deals being executed and know exactly how the potential synergies of these transactions can be realized, incorporated into the firms themselves, and be reflected in the firms' future profits. In this way, we could again see how this may act as a stabilising force in a volatile

market environment.

A noteworthy observation to make here is that when we test for any possible effect of new product approval rates by the FDA on the volatility behavior, we find that contrary to our hypothesis, there is no significant relationship between the two. This is surprising, given how expensive, and labor and time intensive it is to develop a new drug and get it approved through the three phase process as mandated by the FDA. Furthermore, so few drugs actually obtain FDA approval (when phases are compared) that it would seem that such low rates of success might lead to increased volatility due to the high risk of failure and subsequent obvious sunk costs for biopharmaceutical companies. Not only did we expect a positive impact on volatility (meaning it would lead to increased levels of volatility at the firm and industry level), but failures could have a direct impact on shareholders of these publicly traded biopharmaceutical firms, and firms should generally be adverse to bearing this type of risk. However, one could also argue, that shareholders who choose to invest in the biopharmaceutical industry expect these types of transactions and are well-versed in the procedural operations of drug approvals, clinical trials, and patent exclusivity rights that can either guarantee profits, or ensure that those profits are never realized. It seems that the smart investor, when it comes to the pharmaceutical industry and investing in a field that is constantly changing both on the technological front and the regulatory front, should be well-versed in the processes involved in obtaining a return on their investment, i.e. what to expect from the industry itself, how exactly firms make their profits in this industry, and how heavy regulatory measures affect profits and the uncertainty of future profits.

8 Concluding Comments

From our results it is clear that as expected, idiosyncratic volatility at the firm and industry levels is higher than that of the market for the biopharmaceutical industry. The difference persists over time, although the actual levels of each volatility series do not seem to greatly increase or decrease with a linear trend. One point to make here is that Campbell et al. (2001) does in fact observe a linear time trend in the volatility series. This

could perhaps be due to the fact that they had an observation period almost double that which we have for our examined time period, and they look at every possible industry within the market. However, it is worth noting that the average firm level volatility is far higher at all points in our twenty five year time frame than that of the market due to diversification effects. In this paper we attempt to perform an explanatory regression for the behavior of the firm volatility series. For this we include industry-specific variables to ascertain whether or not they have any type of explanatory power that could differentiate the volatility behavior between the market and the pharma firms themselves. The variables we considered controlled for the macroeconomic conditions (whether the year/month was an NBER-dated recession or not) and included the changing business environment characteristics (with the M&A deals count and their total values per month and year). Additionally, we find that these are all significant variables. Using lags of the different variables does not yield significantly different results.

We also find that product approval success rates do not have an effect on the volatility of the average firm. Furthermore, our findings distinguish between the risk the average pharma firm is susceptible to as compared with the level of risk that the big pharma firms are susceptible to. The big pharma firms may pose a better investment to the more passive investor who is simply seeking a return on their investment, as these larger firms have capital buffers with which they can still provide their shareholders with returns and incentives for continued future investment whereas the smaller pharma firms may simply be acquired by the larger firms, or may focus entirely on research and development or may lack resources for significant marketing efforts. Regardless, the smaller firms have different strengths which can either yield an immense payoff if a new desireable product is developed, or can cause these firms to simply fold, given that they may not be able to withstand the prevailing levels of volatility.

It would be worth researching in the future if the volatility levels have in fact caused some firms to fold entirely, or have caused smaller firms to seek being acquired by larger pharma firms with entire marketing departments capable of taking a drug to economic viability. Additional research could also investigate the R&D outsourcing that is conducted by many of the largest big pharma firms, who seek to outsource product development

but still hold the intellectual property rights to whatever compounds may be developed and subsquently approved. It would also be interesting to examine product pipelines in closer detail. For example, noting what patent cliffs would have the largest effects on the volatility levels within the biopharmaceutical industry, or to examine the behavior of the pharma brands and the ensuing behavior of the generics brands that enter the market. Another topic we came across in our research is that of "patent gaming" , meaning that big pharma brands with market exclusivity pay smaller generics brands (who are about to enter the market and undoubtedly absorb a large portion of the product revenue these private pharma brands are relying on) to not actually enter the market for a longer period of time, allowing the brand products to keep profiting immensely off of a single product. Another method pharma brands use is declaring that they have found another type of "off-label use", allowing them to appeal to the FDA for further market exclusivity or extension of a patent given that they had just discovered another use for their products about which they had previously not known, and they should legally be able to benefit from this "new" use. Although we did not examine these topics in our paper, they remain important and controversial areas of business for the biopharmaceutical industry, on the side of the generics, the big pharma brands, and often especially on the side of the regulatory agencies. Anyone who is interested in this industry may find these areas of particular interest to research when looking at biopharmaceutical returns volatilities.

Our original hypotheses held up well regarding the volatility levels between the different volatility series, but did not hold up regarding any linear time trend within each individual volatility series. The second half of our hypothesis, dealing with the explanatory regression, was able to hold up when it came to predicting that the M&A activity in the industry would be significant, but it seemed to affect our numbers in the opposite direction of how we had originally thought it would, though the results are in line with what some researchers find. Regardless, this does have implications for investors. The higher levels of volatility in the biopharmaceutical industry can mean that investors who specialize in that industry must pay closer attention to the day to day happenings regarding how business dealings can affects returns for the numerous pharma firms. Investors should therefore be very active if they are to truly understand and profit from the pharma industry. Passive investors,

however, due to the increased volatility levels, should aim for increased diversification within their portfolios to try and help diversify away the various risks associated with holding biopharmaceutical stocks. The portfolio implications, therefore, are very similar to the implications of an increase in volatility within any industry, and not entirely specific to the pharmaceuticals industry. Since we find that the M&A activity significantly relate to the volatility behavior for the average pharma firm, it will continue to be worth investors' time (and money) to pay attention to the consolidation activity in biopharmaceuticals, especially if over time a trend increase in volatility at the industry level were to appear.

References

Barberis, N. and Huang, M. (2001). Mental accounting, loss aversion, and individual stock returns. *The Journal of Finance*, LVI(4):1247–1292.

Bessembinder, H. and Seguin, P. J. (1992). Futures-trading activity and stock price volatility. *The Journal of Finance*, 47(5):2015–2034.

Bharath, S. T. and Wu, G. (2005). Long-run volatility and risk around mergers and acquisitions.

Buysse, I., Laing, R., and Mantel, A. (2010). The impact of the economic recession on the pharmaceutical sector. *World Health Organization and Universiteit Utrecht*, Centre for Pharmacoepidemiology and Pharmaceutical Policy Analysis.

Campbell, J. Y., Lettau, M., Malkiel, B. G., and Xu, Y. (2001). Have individual stocks become more volatile? an empirical exploration of idiosyncratic risk. *Journal of Finance*, 56:1–43.

Danzon, P. M., Epstein, A., and Nicholson, S. (2004). Mergers and acquisitions in the pharmaceutical and biotech industries. *National Bureau of Economic Research*, Working Paper 10536.

Douglas, G. W. (1969). Risk in equity markets: An empirical appraisal of market efficiency. *Yale Economic Essays*, 9(1):3–45.

Gatti, S. and Chiarella, C. (2013). M&a in uncertain times: Is there still value in growing? *Centre for Applied Research in Finance*, Universitá Bocconi.

Golec, J., Hegde, S., and Vernon, J. (2005). Pharmaceutical stock price reactions to price

constraint threats and firm-level r&d spending. *National Bureau of Economic Research*, Working Paper Series(1129).

Goyal, A. and Santa-Clara, P. (2003). Idiosyncratic risk matters! *The Journal of Finance*, LVIII(No. 3):975–1007.

Hall, B. H., Jaffe, A., and Trajtenberg, M. (2005). Market value and patent citations. *RAND Journal of Economics*, 36(1):16–38.

Higgins, M. J. and Rodriguez, D. (2006). The outsourcing of r&d through acquisitions in the pharmaceutical industry. *Journal of Financial Economics*, 80:351–383.

Lerer, L. and Piper, M. (2003). *Digital Strategies in the Pharmaceutical Industry*. Palgrave Macmillan UK.

Levy, H. (1978). Equilibrium in an imperfect market: A constraint on the number of securities in the portfolio. *The American Economic Review*, 68(4):643–658.

Mayers, D. (1976). Nonmarketable assets, market segmentation, and the level of asset prices. *The Journal of Financial and Quantitative Analysis*, 11(1):1–12.

Mazzucato, M. and Tancioni, M. (2005). Stock price volatility and patent citation dynamics: The case of the pharmaceutical industry.

Merton, R. C. (1980). On estimating the expected return on the market. *The Journal of Financial Economics*, 8:323–361.

Pastor, L. and Veronesi, P. (2004). Was there a nasdaq bubble in the late 1990s? *National Bureau of Economic Research*, NBER Working Paper series.