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School of Economics and Management

Drug Discovery and Development

Does the maturity of biotech companies affect their stock return volatility?

By
Hanna Brännström

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Supervisor:Anders Vilhelmsson

Abstract

Stock return volatility is very high in the biotech industry opposed to other industries and there is limited explanation as to why. Biotech companies invest large amounts of money on research and development to move drugs forward in the clinical trial phases, to get market approval by the regulatory agency FDA. The drug discovery and development process is long and expensive, taking on average 12 years and costing around 2.5 billion USD per new approved drug. In addition, the investments made into moving drugs forward in the trial phases pose great uncertainty due to the unknown outcome and the low success rate of around 6% among the drug candidates. Still it has been suggested that when investing in biotech stocks one should look into the clinical trial data. This raises questions of how great an impact the clinical trials have on the stock return volatility. This study develops a new measure of maturity, from clinical trial data, and is the first study to investigate how the measure affects volatility. To do so, a panel data model with data from 128 biotech companies between 2009-2017 is used. Results show evidence that maturity is positively related to stock return volatility.

Keywords: Stock return volatility, biotech industry, clinical trials, R&D, panel data

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Contents

1 Introduction

Biotech stocks have the potential for high returns, but they carry a lot of risk and are highly volatile. Biotech companies develop drugs, through the use of living organisms, used for treating disease (Amgen 2018). Findings suggest that firms in high-tech industries are exposed to high stock return volatility (Gharbi, Sahut, and Teulon 2014). Biotech, as a high-tech industry, exhibits high stock return volatility and there is limited explanation as to why. Previous literature mostly focuses on other high-tech industries, such as the pharmaceutical (pharma) industry. Mazzucato and Tancioni 2013 studied the pharma industry and found a positive association between stock return volatility and innovation, measured in terms of research and development (R&D) intensity and patents. Findings in an earlier study made by Mazzucato and Tancioni 2008 show that firms with higher R&D intensity also experience higher idiosyncratic (firm-specific) risk. It thus seems that R&D investments make high-tech stocks riskier. Gharbi, Sahut, and Teulon 2014 suggests this is due to the information asymmetry in innovation. The biotech industry is driven by innovation and is very R&D intensive. A firm's R&D spending is money put into investments with the aim to generate something innovative and innovation embodies a lot of uncertainty. Considering that volatility is a measure of investment risk (Zhang 2010), one could therefore hypothesize that the level of innovation should hence affect stock return volatility.

As an investor, both risk and stock returns are important factors to consider when making an investment (Aloui and Jarboui 2018). While risk is a state of uncertainty, stock returns are generated by growth potential of firms. Investing in biotech stocks, where most companies are unprofitable (Thakor et al. 2017) and the outcome of innovation is uncertain, is certainly not easy. Kam 2017 suggests that instead of relying on information in financial statements, one should instead look into clinical trial data. Discovering and developing a drug, and more specifically conducting clinical trials is costly, as the amount of money spent on R&D increases for each phase[1] in the clinical trials. DiMasi, Grabowski, and Hansen 2016 estimates the cost of clinical trials per approved new drug to be 1.46 billion USD. Still, biotech firms spend a large amount of money in moving drugs forward in clinical trials that are required for a drug to be approved by the regulatory agency FDA[2] and become marketable. In addition, the success rate among the drug candidates is low, where approximately 6%[3] of the drugs gets approved by the FDA (FDA 2018c).

The outcomes of clinical trials can work as a catalyst in creating greater returns and attracting investors, or if the outcome is negative, it can instead cause high price drops. In an event study focusing on the release of clinical trial results, conducted on large biopharma companies, failure and success in the trial phases was found to affect stock returns negatively versus positively (Hwang 2013). Furthermore, Thakor et al. 2017 concludes that the performance of biopharma companies is dependent on the set of drug candidates in development. Xu 2006a provides evidence that R&D uncertainty decreases after drugs have entered phase II in clinical trials. She also finds that the biggest contribution to a decrease in volatility is when a drug has entered phase III. Hence, the risk diminishes throughout the trial phases, giving support to that the stock return volatility might be affected by the clinical trials.

1. Clinical trials are divided into three different phases; phase I, phase II and phase III.
2. United States Food and Drug Administration.
3. The success rate was calculated by (0.7x0.33x0.275)x100=6.3525%, in which 0.275 is the median of the drugs making it to be reviewed by the FDA. For more information see FDA 2018c.

This paper contributes to the literature by developing a new measure of maturity, from clinical trial data and is the first study to investigate how the measure affects volatility. The purpose of this study is to evaluate if the maturity of biotech companies affect their stock return volatility.

The remainder of this paper is structured as follows. Section 2 provides a background of the biotech industry and the drug development process. Section 3 reviews the relevant literature on stock return volatility and connects it with the clinical trial phases. Section 4 describes the sample and data used, along with the calculations of the chosen model variables. Section 5 presents the empirical model and the diagnostics tests that were performed to ensure that the model presents accurate results. Section 6 presents the empirical results. Section 7 concludes.

2 Background

2.1 The Biotech Industry

Biotech can be defined in two ways. The first definition is a wide definition and the second one is narrow (Technology Assessment 1991). The wide definition of biotech is, any technique that manipulates the function of living organisms for practical use (Diehl 2018; Szycher 2016). According to this definition, the biotech industry is thousands of years old. Biological processes, like fermentation, were already used 6000-7000 years ago, to brew beer for instance (Burrill 2014). In the 19th century, father of the genetics, Gregor Mendel, cross-bred plants and discovered how dominant and recessive traits are inherited (Buchanan and Weiss 2013). In 1928, Alexander Fleming discovered the penicillin, the world's first antibiotic (Tan and Tatsumura 2015). This definition of biotech thus extends thousands of years back. However, when thinking of the modern biotech industry, it is the narrow definition, referring to "new" biotech, that is being used. For instance, "new" biotech refers to the industrial use of recombinant DNA technology (Technology Assessment 1991), in which the technology was developed in the early 1970s.

The foundation to the modern biotech industry was created in 1973 (Diehl 2018), with the collaboration between the two professors Herb Boyer and Stanley Cohen (Burrill 2014). Together they developed the recombinant DNA technology. It means that DNA from two different species is combined and inserted into a host cell, for example a bacteria cell, which replicates the DNA (Burrill 2014). The development lead to the creation of the world's first biotech company Genentech, founded in 1976 by Boyer and the venture capitalist Robert Swanson (Russo 2003). Investors are often surprised to find out that the biotech industry has a long history (Wolff 2001).

The biotech industry introduced a new approach to drug development than what was already used by the established and often bigger pharma companies. Whereas both industries produce drugs, the primary difference is the basis of the drug. Biotech companies' drugs have a biological basis using living organisms, such as bacteria, while pharma has a chemical basis (Segal 2018). Biotech and pharma further differs in their view of earnings. Thakor et al. 2017 mean that biotech companies are not necessarily focusing on generating earnings, most are in fact unprofitable, instead they invest large amounts on R&D, to reach important milestones in the drug development process. (Thakor et al. 2017), further state that the investments needed for R&D are usually funded by either alliances, mergers and acquisitions or by external financing. By partnering with a larger

pharma company, a biotech company can get the necessary financial support it needs and in return it provides the pharma company with an innovative product that can be manufactured (Burrill 2014).

2.2 The Drug Development Process

2.2.1 Research and Development

A drug needs to pass a series of tests to show that it is safe and efficacious for it to win market approval by the regulatory agency FDA (Burrill 2014). The process of developing, testing and getting FDA approval to sell a drug, is long and takes on average 12 years in the US (Van Norman 2016). The process starts with the discovery and development of the drug, taking around 3-6 years (Burrill 2014). A target disease is chosen, in which the drug is intended to treat, and thereafter possible compounds in the drug are identified. Thousands of compounds are screened in laboratory tests for their ability to affect the chosen target disease (FDA 2018a).

2.2.2 Preclinical Studies

A small number of the thousands of compounds makes it to the preclinical studies, which lasts about 1 year. The drug is being tested in the laboratory and on animals to find out if it is safe to test on humans and hence begin clinical trials (FDA 2018b).

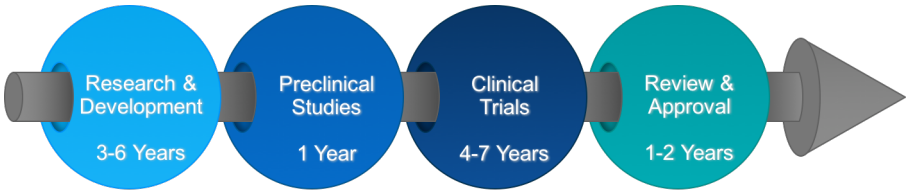
2.2.3 Clinical Trials

Clinical trials take around 4-7 years and are divided into three phases (Burrill 2014). Each phase involves testing a newly developed drug on an increasing number of human participants. The tests in phase I are conducted on healthy volunteers. Whereas tests in phase II and phase III are conducted on people affected by the target disease. The phase I trials are the smallest ones with 20 to 100 participants. The purpose of phase I trials is to determine a drug's safety and the human body's tolerance level to the drug. Around 70 % of the drugs in phase I, which lasts several months, move to the next phase. The phase II trials consist of a greater number of participants, usually several hundred, and lasts many months up to 2 years. Phase II trials test a drug's efficiency and potential side effects (FDA 2018c). The efficiency of the drug being tested, is compared to that of a placebo (Burrill 2014). Around 33 % of the drugs in phase II succeed. Phase III trials last from 1 to 4 years and are the largest trials, with usually several thousand people. The efficacy compared to other treatments is being tested combined with its interaction with other drugs. Around 25-30 % of the drugs in phase III succeed (FDA 2018c).

2.2.4 Review and Approval

If a drug has successfully passed the clinical trials, the drug developer submits a New Drug Application to the FDA (Burrill 2014). FDA reviews the submitted data of the drug's performance in the clinical trials and makes the decision if it is safe to be approved and thus released onto the market (FDA 2018d). Within 10 months of the filing, the FDA is to make a decision (Burrill 2014). Even after the FDA has approved a drug and it has been commercialized, the monitoring of a drug's safety continues (FDA 2018e). The cost of developing a drug that gets market approval is estimated to be just over 2.5 billion USD (DiMasi, Grabowski, and Hansen 2016). Figure 1 shows a summary of the drug development process.

Figure 1: The Drug Development Process



3 Literature Review

3.1 Stock Return Volatility and Clinical Trial Phases

A major topic in financial theory is stock return volatility and thus what causes movements in stock returns. One theory about sources of stock return volatility, referred to by Zhang 2010, is "fundamentals." According to Zhang 2010, "fundamentals", relates to fundamental factors that capture uncertainty about future free cash flow of a company. Different proxies, variables that capture fundamental uncertainty or "earnings uncertainty" (Jankensgård and Vilhelmsson 2018), have been addressed in a number of previous studies. Shan, Taylor, and Walter 2014 uses "other information", defined as information about fundamentals that is not shown in financial statements, as a proxy for future cash flows when explaining its relation with stock return volatility. Their study shows that when current other information is more uncertain, volatility increases. Another contributing factor to increases in volatility is technology advances and its growth opportunities, hence technology intensity (Schwert 2002).

Another proxy is growth options. A growth option is an option for future opportunities that are created through present investments, hence it can only be kept by going through with a given investment opportunity. Thus, a growth option is an increasing function of uncertainty as the value of the growth option is the return earned through investment (Jung and Kwak 2018). Fujiwara 2012 studied growth options for biotech start-ups as a valuation of technological potential in high-tech companies. The present value on the potential of new technology or other innovation was used as a measurement for growth options. By also acknowledging the long drug development process from discovery to commercial markets, Fujiwara 2012 concluded that growth options were important in determining the value of R&D investments. The importance of the growth option as a determinant of the value of investments in R&D was also noted by Jung and Kwak 2018.

That some sectors have fundamentally higher uncertainty about future earnings potential, is supported by Gharbi, Sahut, and Teulon 2014; Thakor et al. 2017, in which studies show that high-tech industries, experience particularly high stock return volatility. Furthermore, Mazzucato and Tancioni 2013 highlights in a study focusing on the pharma industry, the positive relation between innovation on a firm level and stock return volatility, where innovation is defined as R&D intensity and patent related measurement. The intensity of investments in R&D has positive effects on stock return volatility (Chan, Lakonishok, and Sougiannis 2001; Gharbi, Sahut, and Teulon 2014). Whereas Ross, Fisch, and Varga 2017 show that uncertainty is positively related to R&D investments. Mazzucato and Tancioni 2013 base their study on that increases in innovation involves

greater uncertainty about the future growth of a firm, which in turn causes volatility to increase. They further address that uncertainty, thus innovation, and stock returns are connected in the sense that future growth expectations affect stock prices, and innovation itself drives the growth of a firm. A firm's investments in R&D increases when the firm-specific risk return volatility is high (Van Vo and Le 2017). Altogether, the findings in these studies support the belief that stock return volatility and fundamental uncertainty are positively related.

The uncertainty that surrounds the risk and reward of investments in innovation, may be heightened by information uncertainty. According to Guo, Lev, and Zhou 2004 stock return volatility is a measure of information asymmetry. Factors such as firm age (Pástor and Pietro 2003), firm size (Ben-Zion and Shalit 1975; Czarnitzki and Toole 2013) and earnings (Xu 2006b), can affect the information about a firm. Gharbi, Sahut, and Teulon 2014 argues that stocks of high-tech industries become riskier, due to information asymmetry that arises when firms engage in R&D activities. When stocks becomes riskier they also become more volatile (e.g., Guo and Savickas 2006; Peltomäki 2007). In addition, another factor that has been shown to have a relation to stock return volatility is leverage (Jankensgård and Vilhelmsson 2018). Moreover, volatility of equity returns increases with the degree of debt, thus leverage (Christie 1982). For most biotech firms, the leverage is very low, implying that they are largely financed by equity (Xu 2009).

To evaluate biotech firms, where most firms are unprofitable (Thakor et al. 2017), information not stated in financial statements needs to be taken into account. Kam 2017 suggests that most of the value of a biotech company is found in clinical trial data. How does data from clinical trials relate to stock return volatility? Hwang 2013 showed that a failure and success in the different clinical trial phases affect stock returns negatively versus positively. Studies conducted on pharma derived drugs in the US, show that the failure rates decrease, hence the success rate increases, when a drug reaches the next phase in clinical trials (DiMasi 2001; DiMasi, Grabowski, and Hansen 2016). Thus, investing in a drug that is in the early process of development should therefore be more risky than one in late development, because the uncertainty of clinical trial failures diminishes further along in the process.

Due to the similar nature of biotech and pharma and taking into account that biotech firms invest a larger amount of money on R&D, thus innovation, the decrease in uncertainty and risk throughout the clinical trial phases should also apply to biotech firms. Thakor et al. 2017 suggests that firm-specific risk can be whether a drug successfully completes a phase in clinical trials. Furthermore, a superior proxy for innovative activities of biotech firms is, according to Bergeron, Savor, and Kryzanowski 2004, the drug's movement from one phase in clinical trials to another. This proxy was also used by Xu 2009, in defining R&D innovation as the movement of a drug to the next phase. That R&D uncertainty decreases after drugs have entered phase II in clinical trials, and that the biggest decrease in volatility is when a drug has reached phase III, is showed in a study made by Xu 2006a.

The findings in the literature, results in two hypotheses that will be tested in this study. Recall that this study develops a new measure of maturity from clinical trial data. The first hypothesis states that if maturity increases, volatility will decrease. The second hypothesis states that if maturity increases, volatility increases. The arguments behind the two hypotheses are presented in 4.2.2.

4 Sample and Variables

4.1 Sample and Data

The sample consists of 128 biotech companies, which are classified under the sector "healthcare" and industry "biotechnology", and are listed on the stock exchange NASDAQ and have data available in Capital IQ and Compustat. The sample period is 2009-2017. This study is conducted on the US market focusing on biotech companies listed on the second largest stock exchange in the US, NASDAQ. Even though NYSE is the world's largest stock exchange, and the biggest one in the US, it is NASDAQ that has the highest concentration of biotech stocks being traded and clinical trial data is more readily available. In addition, the drug development process is based on information from the regulatory agency FDA, which regulates the drugs in the US. For a company to be included in the sample, it needs to fulfill a set of criteria. Firstly, it must have minimum one drug in clinical trial phases anywhere in the sample period. Secondly, it has to be listed on NASDAQ and be classified as a biotech company. Clinical trial data was obtained from Capital IQ and filtered for companies listed on NASDAQ under the industry classification "pharmaceuticals, biotechnology and life sciences." Since the study is focusing on the stocks of biotech companies, the industry classification had to be narrowed down to only include the biotech industry. This was done by classifying each company obtained from Capital IQ in the clinical trial data, according to the filter used in Yahoo Finance. The original sample consisted of 150 companies, seen in Table 5, Table 6 and Table 7 in the Appendix. A second filter was done by removing all companies belonging to another industry than biotech. Thirdly, the companies had to have financial information and daily closing prices available in Compustat for 2017. The companies that had not were removed from the sample[4]. After filtering for companies that fulfilled the selection criteria, the final sample ended up consisting of 128 biotech companies, as seen in Table 8, Table 9 and Table 10 in the Appendix.

A problem with the sample, which only contains companies with data available for 2017, can be survivorship bias. Companies that are removed from Compustat during the period, are not included in the sample. If a firm preforms badly, for instance defaults, it gets removed from Compustat. Survivorship bias for small firms might be more likely since they are usually more risky and thus more volatile. This can be a possible explanation as to why there was no data available in Compustat for two of the companies in the original sample. The effects of survivorship bias might cause an overestimation of the stock returns for small firms.

4.2 Variables

4.2.1 Volatility

The dependent variable in the sample, volatility (Volatility) is measured as the standard deviation of annual stock returns. Daily closing prices (PRCCD), obtained from Compustat, are converted to daily stock returns by taking the natural logarithm of the closing price today divided by the closing price yesterday. Thereafter the method used by Jankensgård and Vilhelmsson 2018 is adapted in computing the measurement of volatility. The calculated daily stock returns are squared and then the squared terms are summarized over all trading days in a year. To get the estimate of the annualized total volatility, the square root of the calculated sum is taken.

4. Out of 130 remaining companies two were removed from the sample.

4.2.2 Maturity Measure

A unique measure of maturity (MaturityMeasure), is created from clinical trial data. Clinical trial data as it is, only accounts for the number of products in the different trial phases. The created measure accounts for the biotech companies' ability to develop drugs, where a higher number of products in clinical trials show of higher technological advancement. The maturity measure is created given how many products a firm has in the different phases for each year in the sample period. The clinical trial phases are given different weights, where there is assumed that products in phase III show of higher maturity than those in phase I and phase II. For phase I the number of products is multiplied by one. For phase II the number of products is multiplied by two, and for phase III it is multiplied by three. See Table 1 as a reference for how the measure was created. Data was obtained from Capital IQ.

Table 1: Computing the Maturity Measure

The purpose of this table is to show the general idea behind how the MaturityMeasure was computed. Therefore the table only shows a small part (GILD and JAZZ) of the full sample of companies. The MaturityMeasure is computed by taking the sum of the number of products in phase I multiplied with one, in phase II multiplied with two and in phase III multiplied with three, for each year in the sample period.

Stock	Year	Phase I	Phase II	Phase III	Maturity Measure
GILD	2009	5	7	3	28
GILD	2010	5	6	4	29
GILD	2011	5	7	6	37
GILD	2012	6	9	6	42
GILD	2013	5	12	4	41
GILD	2014	0	0	54	162
GILD	2015	0	0	61	183
GILD	2016	0	0	61	183
GILD	2017	0	0	49	147
JAZZ	2009	0	0	0	0
JAZZ	2010	0	0	0	0
JAZZ	2011	0	0	0	0
JAZZ	2012	1	0	1	4
JAZZ	2013	1	0	1	4
JAZZ	2014	2	2	3	15
JAZZ	2015	1	1	3	12
JAZZ	2016	1	2	4	17
JAZZ	2017	2	3	2	14

Arguments for the first hypothesis, if maturity increases, volatility will decrease, are partly based on the findings in Xu 2006a. She showed that the further a drug is in the clinical trials, the more it contributes to a decrease in volatility. Seeing volatility as a risk measure, one can thus assume that also the risk diminishes throughout the trial phases. The other part of the arguments are based on the findings in DiMasi 2001; DiMasi, Grabowski, and Hansen 2016, that the success rate for a drug increases the further it gets in the clinical trial phases. The success rate can account for "other information". In which other information was used by Shan, Taylor, and Walter 2014, which showed that volatility increases when other information is more uncertain. Thus, when the success rate improves the uncertainty should decrease and also volatility. A negative relation between maturity and volatility is therefore expected from the first hypothesis.

Arguments for the second hypothesis, if maturity increases, volatility will increase, are based on the positive association between larger investments in R&D, and increases in volatility (Mazzucato and Tancioni 2013) Thus, the intensity of R&D investment increases stock return volatility (Chan, Lakonishok, and Sougiannis 2001; Gharbi, Sahut, and Teulon 2014). As accounted for, the costs of conducting clinical trials, increases for each phase, which means that more R&D investments are required. Taking consideration that more technological advanced firms have a higher number of drugs in the trial phases and most likely also spend larger amounts on R&D, a positive relation between maturity and volatility is expected from the second hypothesis.

4.2.3 Earnings

A firm-specific variable that has showed to be associated with volatility is earnings (Earnings). The definition of earnings is net income divided by total assets (NI/AT). Financial data was obtained from Compustat. Prior studies show that earnings have a negative relation with stock return volatility (e.g., Jankensgård and Vilhelmsson 2018; Sadka 2007). This study is solely conducted on biotech companies and recalling that most biotech companies are unprofitable, the relation between earnings and volatility might not be true in this study.

4.2.4 Leverage

Another firm-specific factor that is associated with stock return volatility is leverage (Dennis and Strickland 2004), in the sense that volatility of equity returns increases from leverage (Christie 1982). However, leverage for most biotech firms is very low, implying that they are largely financed by equity (Xu 2009). Leverage is computed as total liabilities divided by total assets (LT/AT) and data was collected from Compustat.

4.2.5 Size

Firm size is often mentioned as an important factor in determining stock returns. Banz 1981 noted that the average return tends to be greater for small firms than for large firms. The effect of firm size on stock returns was also confirmed by Fama and French 1996 which noted a negative relation between the size of a company and its stock return. Furthermore, firm size relates to the information environment of a company (Embong, Mohd-Saleh, and Sabri Hassan 2012) and is also associated with risk, where stocks of smaller firms generates higher returns to compensate for the greater risk (Gallizo and Salvador 2006). Thus, the size of a company matters and a negative relation between firm size and stock returns is expected. Firm size (Size) is calculated by taking the natural logarithm of a firm's total assets (AT). Data is obtained from Compustat.

4.2.6 Return on Research Capital

Return volatility has a positive relation with R&D intensity (Chan, Lakonishok, and Sougiannis 2001). In addition, R&D intensity measured as R&D expenditures divided by sales has been used as a proxy for innovation. Innovation itself is associated with uncertainty, because it changes the status quo (Mazzucato 2006). Because of the biotech industries high spendings on R&D, it is therefore of interest to use a proxy that captures the intensity of R&D. In this study a proxy for R&D intensity will be return on research capital (RORC), calculated as dividing the current year gross profit (GP) by the previous year R&D expenditures (XRD). Data was collected from Compustat. Mazzucato

2006 further address that measuring R&D intensity in a similar manner as in this study, will only capture the innovation input and not the actual results of innovation. Hence, to also account for the output of innovation additional proxies will have to be considered, see 4.2.9, 4.2.10.

4.2.7 Price/Earnings to Growth Ratio

Generally companies with a high price/earnings (P/E) ratio compared with a low, are more desirable for investors due to a firms higher earnings growth rate. However, since most biotech firms, have negative earnings, the P/E ratio is not fitting when evaluating biotech stocks. A suitable measure is instead the price/earnings to growth ratio (PEG) (Keegan 2009). Data to compute the PEG ratio was collected from Compustat. The PEG ratio is calculated by dividing a company's P/E (PRCC_F/EPSPI) by its annual growth in earnings per share (NI/CSHO). A PEG ratio of one, indicates that a stock is fairly valued, whereas an undervalued respectively overvalued stock would have a PEG less respectively more than one (Chilung 2002).

4.2.8 Quick Ratio

The quick ratio (QuickR) is a liquidity ratio and shows the relationship between liquid assets and current liabilities, where firms with a positive liquidity position shows high ratio values (Bolek and Wolski 2012). Furthermore, liquidity, stock returns and volatility are connected. Liquidity has shown to have a positive impact on volatility (Chen et al. 2013), where illiquid stocks tend to have a higher stock return volatility (Acharya and Pedersen 2005). QuickR was calculated by taking the difference between total current assets and total inventories divided by current total liabilities (ACT-INVT)/LCT. Data was obtained from Compustat.

4.2.9 Number of Products Approved

As previously mentioned in 4.2.6, proxies that can account for the output of innovation need to be considered. Therefore the aim with including the variable number of products approved (Nrproductsapproved), is to account for real outputs of innovation. Considering that each drug approved by the FDA is somewhat innovative, the variable Nrproductsapproved might work as a proxy and thus show a significant relationship with stock return volatility. Nrproductsapproved accounts for how many of the products in the drug development process that got approved by FDA. Data was collected from Capital IQ.

4.2.10 Number of Products in R&D

The variable number of products in R&D (NrproductsinR&D) is chosen because it might work as a proxy for R&D intensity. Recall that R&D intensity has been shown to be positively related to stock return volatility (Chan, Lakonishok, and Sougiannis 2001; Gharbi, Sahut, and Teulon 2014). In addition, also recall that the drug development process begins with research and development. Investments done in R&D should result in a stronger R&D progress and thus a higher number of products in R&D. But it might not always be favorable to have a lot of products in R&D, since a biotech firm also has to focus on moving drugs forward in clinical trials where the real progress is made. Thus, a possible relation between the variables NrproductsinR&D and Volatility could therefore as well be negative. Data was obtained from Capital IQ.

5 Empirical Model

5.1 Panel Data

The data set used in this study is unbalanced panel data. Panel data consists of both time series and cross-sectional data, thus it allows the explanatory variables to vary through individuals and time (Verbeek 2012). Panel data can either be estimated through the assumption of fixed effects or random effects. To help decide between fixed effects or random effects panel data model, a Hausman test can be performed. The Hausman test tests whether estimators for the fixed effects and random effects are significantly different. Thus, the null hypothesis states that only the random effects estimator is consistent, whereas the fixed effects estimator is consistent under both the null- and the alternative hypothesis (Verbeek 2012). Given the result from the Hausman test, see Table 13 in the Appendix, the null hypothesis is rejected and the fixed effects model is applied.

5.2 Diagnostic Tests

5.2.1 Stationary

As a first step before running the regressions, stationarity is examined. It is important that time series data is stationary, hence the mean and variance is constant over time, to not cause a spurious regression (Enders 2008). Since panel data is a combination of time series- and cross-sectional data, one should test for stationarity (Brooks 2014), for this a unit root test can be performed (Verbeek 2012). There are several panel data unit root tests, in which all tests for the presence of a unit root in multiple series. Panel unit root tests, like the Fisher-ADF test, allows for the panels to be unbalanced (StataCorp 2018). Due to having an unbalanced sample the Fisher-ADF test is run.[5]

5.2.2 Multicollinearity

Multicollinearity arises when the correlation between two independent variables in the model is too high. A correlation that is too high causes inaccurate estimates of the highly correlated variable such as large standard errors and coefficients with unpredictable signs (Verbeek 2012). A coefficient with large standard errors is less likely to be significant, thus multicollinearity undermines the statistical significance of the highly correlated variable (Allen 1997). To detect multicollinearity a variance inflation factor (VIF) test can be conducted, where the VIF for each independent variable is computed (Verbeek 2012). A VIF between four and ten indicates collinearity (Salmerón, Garcıa, and Garcıa 2018). Equation 1 shows how the VIF is calculated, where R-squared is the squared multiple correlation coefficient between two variables (Verbeek 2012).

$$VIF = \frac{1}{1 - R^2} \tag{1}$$

5. The Fisher-ADF test combines p-values from four independent unit root tests. By looking at the p-values from the four individual unit root tests, the null hypothesis stating that all panels contain a unit root, is either rejected or accepted. Rejecting the null hypothesis of a unit root means that the sample is stationary (StataCorp 2018).

Another way of detecting multicollinearity is to compute a correlation matrix and examine the correlation between the independent variables. A correlation coefficient higher than 0.7 hints multicollinearity. To ensure that multicollinearity is not a problem, both a VIF test and an examination of the correlation matrix is performed.

5.2.3 Heteroskedasticity and Autocorrelation

The problem of heteroskedasticity arises if the variance of the error term differs. Even though the estimators remain unbiased they become less efficient and the standard errors will be wrong (Verbeek 2012). To test for heteroskedasticity in fixed effects models, the modified Wald test can be applied. Under the null hypothesis the error terms has the same variance, they are thus homoscedastic (Baum et al. 2001).

Autocorrelation emerges when error terms are correlated over time, this causes inaccurate standard errors and therefore the results becomes inefficient (Verbeek 2012). The Wooldridge test for autocorrelation in random-or fixed-effects one-way models, can be applied, in which the null hypothesis states there is no autocorrelation (Drukker et al. 2003). To assure that the regressed estimators' standard errors are accurate, under either or both autocorrelation and heteroskedasticity, robust standard errors should be used (Verbeek 2012).

5.3 Model Specification

The empirical model is a unbalanced panel data model, consisting of the variables presented in 4.2. The dependent variable is stock return volatility (Volatility). Of the independent variables, MaturityMeasure is the variable of interest, because of the purpose of this study is to investigate if the maturity affect volatility. The other independent variables such as firm-specific factors and additional measures, are added as control variables. All independent variables are measured on year end basis whereas volatility is estimated on daily stock returns. To account for this the approach in Jankensgård and Vilhelmsson 2018 is followed and all independent variables are lagged one period. Equation 2 shows the full model.

$$\begin{aligned}\text{Volatility}_{it} = \alpha_i + d_t + \beta_0 + \beta_1 \text{MaturityMeasure}_{it-1} + \beta_2 \text{Earnings}_{it-1} + \beta_3 \text{Leverage}_{it-1} \\ + \beta_4 \text{Size}_{it-1} + \beta_5 \text{RORC}_{it-1} + \beta_6 \text{PEG}_{it-1} \\ + \beta_7 \text{QuickR}_{it-1} + \beta_8 \text{Nrproductsapproved}_{it-1} \\ + \beta_9 \text{NrproductsinR\&D}_{it-1} + u_{it}\end{aligned} \tag{2}$$

where i refers to the individual company at time t. Furthermore, α_i is the industry fixed effects, d_t is the period fixed effects, included in order to control for factors varying over time, and u_{it} is robust standard errors to control for heteroskedasticity. Since the ambition with this paper is to identify the possible effect maturity has on stock return volatility, the coefficient of interest is β_1.

6 Empirical Results

6.1 Diagnostic Tests

To test for stationarity the Fisher-ADF test is performed. Based on the test results, seen in Table 11 in the Appendix, all four tests for each variable strongly rejects the null hypothesis of a unit root. Thus, stationarity is confirmed. To ensure that multicollinearity does not cause incorrect parameter estimates, a VIF test is conducted. Table 12 in the Appendix shows that none of the variables' VIF exceed four, indicating that multicollinearity is not an issue. A modified Wald test and a Wooldridge test are performed to check for heteroskedasticity respectively autocorrelation. Table 13 in the Appendix, shows low probability values for both tests. Despite this the null hypothesis of no autocorrelation cannot be rejected on a 1 % significance level. The model therefore only experiences heteroskedasticity. To control for heteroskedasticity, the regression model is estimated using robust standard errors.

6.2 Descriptive Statistics

Table 2 summarizes descriptive statistics for the independent variables in Equation 2. On average, Earnings are negative, confirming the general assumption that most of the biotech companies are unprofitable. The biotech companies in the sample have on average less than one approved product, i.e. drug, and less than one drug in R&D. It is possible to conclude that due to the wide range of the MaturityMeasure, most of the drugs of the biotech companies are in the clinical trials. The wide range of the MaturityMeasure and Size, indicates it is a diversified sample with both small and large firms.

Table 2: Descriptive Statistics, 2009-2017

This table shows descriptive statistics for the full sample of 128 biotech companies from 2009 to 2017. MaturityMeasure is the sum of the number of products in phase I, phase II and phase III, multiplied with one, two and three. Earnings is net income divided by total assets. Leverage is a firms total liabilities divided by total assets. Size is the natural logarithm of total assets. RORC is a firms current gross profits divided by previous years RD expenditures. PEG is the price per earnings ratio divided by the earnings growth ratio. QuickR is the difference between total current assets and total inventories divided by current total liabilities. Nrproductsapproved is the number of products approved. NrproductsinR&D is the number of products in research and development.

Variable	Mean	Median	Max	Min	*SD*	*N*
MaturityMeasure	9.193	6.000	183.000	0.000	15.782	1152
Earnings	-0.600	-0.349	0.934	-8.483	1.072	887
Leverage	0.670	0.375	19.538	0.016	1.251	878
Size	4.883	4.846	11.289	-2.442	1.994	878
RORC	0.797	0.000	79.284	-12.574	6.356	852
PEG	0.242	0.000	78.069	-27.607	3.7923	832
QuickR	6.620	4.244	91.575	0.000	7.724	866
Nrproductsapproved	0.128	0.000	6.000	0.000	0.490	1152
NrproductsinR&D	0.422	0.000	31.000	0.000	2.590	1152

Table 3 presents a correlation matrix with coefficients for the variables presented in 4.2. The closer a coefficient is to 1.000, the higher the correlation is, indicating that multicollinearity is a problem. MaturityMeasure, Earnings, Size, RORC, PEG, Nrproductsapproved and NrproductsinR&D are all negatively correlated with volatility. Whereas Leverage and QuickR are positively correlated with volatility. The highest correlation with volatility has Size (-0.3619). Several of the independent variables are correlated. Leverage and Size both show relatively high correlation with Earnings. Out of all the variables, MaturityMeasure and Size has the highest correlation of 0.5787. Thus, for no variable the coefficient is over 0.7, meaning that the sample is not affected by multicollinearity.

6.3 Results

Table 14 in the Appendix reports the findings, before adding control variables, when checking for a relationship between MaturityMeasure and Volatility. Model (1) and Model (2) show a negative significant coefficient for MaturityMeasure, thus volatility decreases when the maturity increases. However, neither Model (3) nor Model (4) show significant coefficients for MaturityMeasure and cannot provide evidence of the maturity having impact on stock return volatility. For the two models that showed a significance for MaturityMeasure the explanatory power is weak, although the explanatory power of Model (2) is better. Accounting for this, period fixed effects are applied, and industry fixed effects are excluded. It is not that surprising to not find any effect with industry fixed effects since most of the variation in volatility and maturity is between and not within companies.

Furthermore, control variables are added in groups as shown in Table 4. In Model (5) the firm-specific variable Size and all the product variables are added. The coefficient for MaturityMeasure is positively significant with Volatility, on a 10 % significance level. This means that an increase in the maturity causes stock return volatility to decrease. Not surprisingly the explanatory power of the model improved significantly when adding control variables. Out of the control variables Size is significant on a 1 % significance level, with a negative coefficient. The size of a firm thus has a negative relationship to stock return volatility. This means that when the size of the company grows, the stock return volatility will decrease. The variable NrproductsinR&D also shows a negative coefficient, being significant on a 1% significance level. An increase in the number of products a firm has in R&D, will decrease the stock return volatility. As for the coefficient of Nrproductsapproved, it is not significant and the stock return volatility is thus not affected by the number of approved products.

In Model (6), the firm-specific variables Earnings and Leverage have been added to the regression. Adding additional two more control variables further improves the explanatory power of the model. Where now 16.7% of the variation in stock return volatility is explained by the explanatory variables. The MaturityMeasure is now significant on a 5 % level. Neither Leverage or Earnings are significant, even though the signs (-) are as expected according to previous studies. The coefficient for Size remains significant, so does the number of products in R&D. The variable Nrproductsapproved shows of no significance.

In Model (7) all control variables have been added. Period fixed effects has been removed, causing the explanatory power to decrease. MaturityMeasure remains positively significant, thus now again on a 10% significance level. Size remains negatively significant, still on a steady 1% significance level. MaturityMeasure and Size remains significant when running the full model, pro-

Table 3: Correlation Matrix for All Variables

This table presents the correlation coefficients for the variables presented in 4.2.

Variable	1	2	3	4	5	6	7	8	9	10
1. Volatility	1.0000									
2. MaturityMeasure	-0.1498	1.0000								
3. Earnings	-0.2995	0.1750	1.0000							
4. Leverage	0.0935	0.0064	-0.5582	1.0000						
5. Size	-0.3619	0.5787	0.5525	-0.2415	1.0000					
6. RORC	-0.1353	0.0763	0.2055	-0.0318	0.2616	1.0000				
7. PEG	-0.0076	0.0953	0.0316	0.0067	0.0553	0.0191	1.0000			
8. QuickR	0.0327	-0.1264	0.1489	-0.2724	-0.0132	-0.1668	-0.0158	1.0000		
9. Nrproductsapproved	-0.1407	0.4753	0.1486	0.0154	0.4741	0.0872	0.1195	-0.1469	1.0000	
10. NrproductsinR&D	-0.0773	-0.0865	0.0788	0.0086	0.0428	0.1185	0.0607	-0.0138	0.0314	1.0000

viding evidence that both variables, have impact on stock return volatility. The coefficient for NrproductsinR&D also remains negatively significant, thus now on a 5% significance level, also providing evidence of having an impact on the volatility of stock returns. The control variables that measure performance of a firm, RORC, PEG and QuickR show no significant coefficient and one can therefore conclude that they do not affect the volatility. Nrproductsapproved, Leverage and Earnings remain insignificant, meaning that they do not affect the volatility in this study.

In Model (8), period fixed effects have been added again and industry fixed effects has been removed since it worsened the models explanatory power. The significance nor insignificance of any of the variables has changed. Only the variables being significant throughout all the regressions in table 4, MaturityMeasure, Size and NrproductsinR&D, are being applied in Model (9).

In Model (9), the significance level remains the same for MaturityMeasure and Size, whereas it improves for NrproductsinR&D. The variable NrproductsinR&D is now significant on a 1% significance level, as it was in Model (5) and Model (6). As expected, the explanatory power decreases when removing most of the control variables. Summarizing the results from the regressions on volatility on the different explanatory variables, shows that Model (8) is most accurate and has the highest explanatory power, in which 19.5% of the variation in stock return volatility is explained by the explanatory variables.

Table 4: Regression Results From Adding Control Variables

This table presents the coefficients, when adding control variables, in different regressions of stock return volatility on the explanatory variables. All explanatory variables are lagged one year. All models are regressed with robust standard errors.

Variables	(5) Volatility	(6) Volatility	(7) Volatility	(8) Volatility	(9) Volatility
MaturityMeasure	0.002*	0.002**	0.002*	0.002*	0.002*
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
Earnings		-0.011	-0.126	-0.114	
		(0.04)	(0.08)	(0.08)	
Leverage		-0.025	-0.038	-0.031	
		(0.04)	(0.03)	(0.03)	
Size	-0.111***	-0.116***	-0.090***	-0.095***	-0.110***
	(0.02)	(0.02)	(0.02)	(0.02)	(0.01)
RORC			-0.001	-0.001	
			(0.00)	(0.00)	
PEG			0.002	0.003	
			(0.00)	(0.00)	
QuickR			0.003	0.003	
			(0.00)	(0.00)	
Nrproductsapproved	0.012	0.018	0.016	0.009	
	(0.03)	(0.03)	(0.02)	(0.03)	
NrproductsinR&D	-0.009***	-0.008***	-0.007**	-0.007**	-0.008***
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
Constant	1.612***	1.640***	1.130***	1.464***	1.608***
	(0.13)	(0.14)	(0.12)	(0.16)	(0.13)
Period fixed	Yes	Yes	No	Yes	Yes
Firm fixed	No	No	No	No	No
N	720	719	679	679	720
R^2	0.164	0.167	0.157	0.195	0.163

Robust standard errors in parentheses
* p<0.10, ** p<0.05, *** p<0.01

6.4 Analysis

The results report evidence of the created measure of maturity, as in the weighted sum of products in clinical trial phases, having positive effects on stock return volatility. The first hypothesis is therefore rejected, while the second hypothesis is accepted. The measure of maturity assigns the clinical trial phases different values and adds the number of products in the trial phases each year during the sample period. This measure thus aimed to account for that larger biotech companies have a higher number of drugs in the trial phases, which can be a sign of them being more technologically advanced. If considering maturity as a measure of technology advances, the findings are in line with the ones in Schwert 2002, who identified that technology advances and its growth opportunities have an increasing effect on volatility. The positive relation might also be explained with the idea behind growth options as a proxy for earnings uncertainty. By making an investment decision today, the value of the growth option increases, but also the uncertainty (Jung and Kwak 2018). One can think of it as if the investment will generate earnings or not. Considering that each trial phase requires larger amounts of investments, there is also more at stake if a drug fails further in the trial phases instead of in the beginning of the trial phases. However, this argument contradicts the evidence that the success rate of a drug increases the further it gets in the trial phases (DiMasi 2001; DiMasi, Grabowski, and Hansen 2016) and thus the diminishing pattern of risk (Xu 2006a).

A relatively natural explanation for the maturity to not show negative effects on volatility, is that the measure does not treat each phase individually. Furthermore, if the growth options increase, the value of R&D investments should increase in line with the finding in Fujiwara 2012. The amount of R&D investments has been found to have positive effects on stock return volatility (Chan, Lakonishok, and Sougiannis 2001; Gharbi, Sahut, and Teulon 2014). To take it a step further, uncertainty is positively related to R&D investment (Ross, Fisch, and Varga 2017). This positive relation also holds for innovation as measured in terms of R&D intensity (Mazzucato and Tancioni 2013). A proxy used for innovative activities in biotech firms has been a drugs movement through the trial phases (Bergeron, Savor, and Kryzanowski 2004). Generally speaking, all biotech companies are highly R&D intensive. An increase in maturity, as in technological advancement, can be seen as an increase in the number of drugs in clinical trials, and thus R&D activity. Taken together, this would result in a greater output of innovation. As we know, innovation carries uncertainty and higher levels of R&D activity can therefore increase the information asymmetry, hence a possible explanation to the positive effects on stock return volatility.

In addition, a reason stock return volatility may increase due to the higher number of drugs in clinical trials, is the higher likelihood of bad news from a drug failing. If a company has more drugs in clinical trials, there is a higher likelihood that a drug fails and transmits bad news causing a decline in the stock price. Even though the significance level of 10% is low, the positive relation can still be interpreted as an increase in the number of drugs in clinical trials, increases the stock return volatility of biotech stocks.

As for the control variables, Size is significant at the 1% level with a negative sign in all models. Thus, the size of a firm has negative effects on stock return volatility. This means that when the size of the company grows, the stock return volatility will decrease. Small biotech firms thus experience more stock return volatility compared to larger ones. The negative relation is in line with previous studies on stock returns (Fama and French 1996; Banz 1981). The results also address the

information environment of a firm and returns relation with risk, in which stocks of small firms are riskier but experience greater returns as opposed to stocks of larger firms (Embong, Mohd-Saleh, and Sabri Hassan 2012; (Gallizo and Salvador 2006). Factors such as firm size, thus affects the information uncertainty, in which stock return volatility decreases when the size of a firm increases.

The control variable, NrproductsinR&D is negatively significant throughout all regressions. The aim with including the variable was for it to work as a proxy for R&D intensity. Thakor et al. 2017 mentions that the performance of biopharma companies is dependent on the set of drugs in development. Recall that the drug development process begins with research and development. A possible explanation to the negative effect on stock return volatility, might be that an increase in the number of products in R&D, signals that a biotech firm is doing well. This would therefore lead to less information asymmetry which causes uncertainty, that in turn increases stock return volatility. The results point towards that the different stages in the drug development process impacts stock return volatility differently.

7 Conclusion

The purpose of this study was to evaluate if the maturity of biotech companies affect their stock return volatility. To do so, a new measure of maturity, from clinical trial data, was developed. Results show that maturity positively affects stock return volatility. To account for technological advancement, the maturity measure adds different weight to the number of drugs in the clinical trial phases. Moving a drug forward in the trial phases requires increasing amounts of R&D investments, combined with a high risk of failure. This is a possible explanation to the positive association between maturity and volatility. However, it is to be noted that the coefficient of maturity is low and that the explanatory power of the model is not that high either. This could be improved by a deeper study of the content of the maturity parameter and a further investigation on the impact of the different clinical trial phases. Different weights can be assigned to the trial phases or one can account for if similar drugs are already out on the market. The foundation to a new measure of maturity was created in this study, and further studies can continue developing the measure. One thing for sure is that clinical trial data is worth understanding when trading biotech stocks. Considering that the different stages in the drug development process had different impacts on stock return volatility, it would be interesting to create a measure of maturity based on the whole drug development process.

What do these findings mean for an investor in biotech stocks? When dealing with biotech stocks it is good to remember that they are highly volatile, only a few are profitable and that the investments in R&D activities are high. Having this in mind, it might not be profitable to only rely on financial measures but to also take into consideration the number of drugs in clinical trials. To answer the question if investors should be wary of investing in biotech companies with many drugs in clinical trials, further studies in the same area are needed. The implication from the findings in this study however suggest that a company that is more technologically advanced (more drugs in clinical trials) has a more volatile stock return, which might lead to a more riskier investment.

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9 Appendix

Table 5: Part 1 - Original Number of Companies from Capital IQ

Company	Ticker	Sector	Industry
1. ACADIA Pharmaceuticals Inc.	ACAD	Healthcare	Biotechnology
2. Achieve Life Sciences, Inc.	ACHV	Healthcare	Biotechnology
3. AC Immune SA	ACIU	Healthcare	Biotechnology
4. Adamis Pharmaceuticals Corporation	ADMP	Healthcare	Drug Manufacturers - Specialty & Generic
5. Adamas Pharmaceuticals, Inc.	ADMS	Healthcare	Drug Manufacturers - Specialty & Generic
6. Advaxis, Inc.	ADXS	Healthcare	Biotechnology
7. Aerie Pharmaceuticals, Inc.	AERI	Healthcare	Drug Manufacturers - Major
8. Agios Pharmaceuticals, Inc.	AGIO	Healthcare	Biotechnology
9. Agile Therapeutics, Inc.	AGRX	Healthcare	Drug Manufacturers - Specialty & Generic
10. Aimmune Therapeutics, Inc.	AIMT	Healthcare	Biotechnology
11. Akebia Therapeutics, Inc.	AKBA	Healthcare	Biotechnology
12. Akcea Therapeutics, Inc.	AKCA	Healthcare	Biotechnology
13. Albireo Pharma, Inc.	ALBO	Healthcare	Biotechnology
14. Alder Biopharmaceuticals, Inc.	ALDR	Healthcare	Biotechnology
15. Alkermes plc	ALKS	Healthcare	Biotechnology
16. Alnylam Pharmaceuticals, Inc.	ALNY	Healthcare	Biotechnology
17. Alexion Pharmaceuticals, Inc.	ALXN	Healthcare	Biotechnology
18. AMAG Pharmaceuticals, Inc.	AMAG	Healthcare	Biotechnology
19. Amgen Inc.	AMGN	Healthcare	Biotechnology
20. Anthera Pharmaceuticals, Inc.	ANTH	Healthcare	Biotechnology
21. Aquinox Pharmaceuticals, Inc.	AQXP	Healthcare	Drug Manufacturers - Specialty & Generic
22. Ardelyx, Inc.	ARDX	Healthcare	Biotechnology
23. Arena Pharmaceuticals, Inc.	ARNA	Healthcare	Biotechnology
24. ArQule, Inc.	ARQL	Healthcare	Biotechnology
25. Array BioPharma Inc.	ARRY	Healthcare	Biotechnology
26. Atara Biotherapeutics, Inc.	ATRA	Healthcare	Biotechnology
27. Avenue Therapeutics, Inc.	ATXI	Healthcare	Drug Manufacturers - Specialty & Generic
28. Avadel Pharmaceuticals plc	AVDL	Healthcare	Biotechnology
29. AVEO Pharmaceuticals, Inc.	AVEO	Healthcare	Biotechnology
30. Axovant Sciences Ltd.	AXON	Healthcare	Biotechnology
31. Axsome Therapeutics, Inc.	AXSM	Healthcare	Biotechnology
32. BioCryst Pharmaceuticals, Inc.	BCRX	Healthcare	Biotechnology
33. BeiGene, Ltd.	BGNE	Healthcare	Biotechnology
34. Biogen Inc.	BIIB	Healthcare	Biotechnology
35. bluebird bio, Inc.	BLUE	Healthcare	Biotechnology
36. BioMarin Pharmaceutical Inc.	BMRN	Healthcare	Biotechnology
37. Blueprint Medicines Corporation	BPMC	Healthcare	Biotechnology
38. Cara Therapeutics, Inc.	CARA	Healthcare	Biotechnology
39. China Biologic Products Holdings, Inc.	CBPO	Healthcare	Biotechnology
40. ChemoCentryx, Inc.	CCXI	Healthcare	Biotechnology

Table 6: Part 2 - Original Number of Companies from Capital IQ

Company	Ticker	Sector	Industry
41. Celgene Corporation	CELG	Healthcare	Biotechnology
42. Cerus Corporation	CERS	Healthcare	Biotechnology
43. Coherus BioSciences, Inc.	CHRS	Healthcare	Biotechnology
44. Clearside Biomedical, Inc.	CLSD	Healthcare	Biotechnology
45. Clovis Oncology, Inc.	CLVS	Healthcare	Biotechnology
46. Clementia Pharmaceuticals Inc.	CMTA	Healthcare	Biotechnology
47. Concert Pharmaceuticals, Inc.	CNCE	Healthcare	Biotechnology
48. Catalyst Pharmaceuticals, Inc.	CPRX	Healthcare	Drug Manufacturers - Specialty & Generic
49. Corbus Pharmaceuticals Holdings, Inc.	CRBP	Healthcare	Biotechnology
50. CTI BioPharma Corp.	CTIC	Healthcare	Biotechnology
51. ContraVir Pharmaceuticals, Inc.	CTRV	Healthcare	Biotechnology
52. Cytokinetics, Incorporated	CYTK	Healthcare	Biotechnology
53. CytRx Corporation	CYTR	Healthcare	Biotechnology
54. Dermira, Inc.	DERM	Healthcare	Biotechnology
55. DelMar Pharmaceuticals, Inc.	DMPI	Healthcare	Biotechnology
56. Dova Pharmaceuticals, Inc.	DOVA	Healthcare	Biotechnology
57. DURECT Corporation	DRRX	Healthcare	Drug Manufacturers - Specialty & Generic
58. Auris Medical Holding AG	EARS	Healthcare	Biotechnology
59. Edge Therapeutics, Inc.	EDGE	Healthcare	Biotechnology
60. Egalet Corporation	EGLT	Healthcare	Biotechnology
61. Evofem Biosciences, Inc.	EVFM	Healthcare	Biotechnology
62. Evoke Pharma, Inc.	EVOK	Healthcare	Drug Manufacturers - Specialty & Generic
63. Exelixis, Inc.	EXEL	Healthcare	Biotechnology
64. EyeGate Pharmaceuticals, Inc.	EYEG	Healthcare	Biotechnology
65. Flexion Therapeutics, Inc.	FLXN	Healthcare	Drug Manufacturers - Specialty & Generic
66. Amicus Therapeutics, Inc.	FOLD	Healthcare	Biotechnology
67. Global Blood Therapeutics, Inc.	GBT	Healthcare	Biotechnology
68. Geron Corporation	GERN	Healthcare	Biotechnology
69. Gilead Sciences, Inc.	GILD	Healthcare	Biotechnology
70. GlycoMimetics, Inc.	GLYC	Healthcare	Biotechnology
71. Genocea Biosciences, Inc.	GNCA	Healthcare	Biotechnology
72. GW Pharmaceuticals plc	GWPH	Healthcare	Drug Manufacturers - Major
73. Halozyme Therapeutics, Inc.	HALO	Healthcare	Biotechnology
74. Heron Therapeutics, Inc.	HRTX	Healthcare	Drug Manufacturers - Specialty & Generic
75. Histogenics Corporation	HSGX	Healthcare	Biotechnology
76. Horizon Pharma Public Limited Company	HZNP	Healthcare	Drug Manufacturers - Specialty & Generic
77. Intercept Pharmaceuticals, Inc.	ICPT	Healthcare	Biotechnology
78. ImmunoGen, Inc.	IMGN	Healthcare	Biotechnology
79. Immunomedics, Inc.	IMMU	Healthcare	Biotechnology
80. Incyte Corporation	INCY	Healthcare	Biotechnology
81. Inovio Pharmaceuticals, Inc.	INO	Healthcare	Biotechnology
82. Insmed Incorporated	INSM	Healthcare	Biotechnology
83. INSYS Therapeutics, Inc.	INSY	Healthcare	Biotechnology
84. Ionis Pharmaceuticals, Inc.	IONS	Healthcare	Biotechnology
85. Intra-Cellular Therapies, Inc.	ITCI	Healthcare	Biotechnology
86. Jazz Pharmaceuticals plc	JAZZ	Healthcare	Biotechnology
87. Karyopharm Therapeutics Inc.	KPTI	Healthcare	Drug Manufacturers - Specialty & Generic
88. Ligand Pharmaceuticals Incorporated	LGND	Healthcare	Biotechnology
89. Lexicon Pharmaceuticals, Inc.	LXRX	Healthcare	Biotechnology
90. Seres Therapeutics, Inc.	MCRB	Healthcare	Biotechnology
91. The Medicines Company	MDCO	Healthcare	Drug Manufacturers - Specialty & Generic
92. MediWound Ltd.	MDWD	Healthcare	Biotechnology
93. MacroGenics, Inc.	MGNX	Healthcare	Biotechnology
94. Melinta Therapeutics, Inc.	MLNT	Healthcare	Biotechnology
95. Momenta Pharmaceuticals, Inc.	MNTA	Healthcare	Drug Manufacturers - Specialty & Generic

Table 7: Part 3 - Original Number of Companies from Capital IQ

Company	Ticker	Sector	Industry
96. Neurocrine Biosciences, Inc.	NBIX	Healthcare	Biotechnology
97. Nabriva Therapeutics plc	NBRV	Healthcare	Biotechnology
98. NuCana plc	NCNA	Healthcare	Biotechnology
99. Minerva Neurosciences, Inc.	NERV	Healthcare	Biotechnology
100. Nektar Therapeutics	NKTR	Healthcare	Biotechnology
101. NewLink Genetics Corporation	NLNK	Healthcare	Biotechnology
102. Novavax, Inc.	NVAX	Healthcare	Biotechnology
103. ObsEva SA	OBSV	Healthcare	Biotechnology
104. Ocular Therapeutix, Inc.	OCUL	Healthcare	Biotechnology
105. OHR Pharmaceutical, Inc.	OHRP	Healthcare	Biotechnology
106. Omeros Corporation	OMER	Healthcare	Biotechnology
107. Onconova Therapeutics, Inc.	ONTX	Healthcare	Biotechnology
108. Otonomy, Inc.	OTIC	Healthcare	Biotechnology
109. Puma Biotechnology, Inc.	PBYI	Healthcare	Biotechnology
110. Pacira Pharmaceuticals, Inc.	PCRX	Healthcare	Drug Manufacturers - Specialty & Generic
111. Progenics Pharmaceuticals, Inc.	PGNX	Healthcare	Biotechnology
112. Prothena Corporation plc	PRTA	Healthcare	Biotechnology
113. Proteon Therapeutics, Inc.	PRTO	Healthcare	Biotechnology
114. Proteostasis Therapeutics, Inc.	PTI	Healthcare	Biotechnology
115. Ultragenyx Pharmaceutical Inc.	RARE	Healthcare	Biotechnology
116. Regeneron Pharmaceuticals, Inc.	REGN	Healthcare	Biotechnology
117. Reata Pharmaceuticals, Inc.	RETA	Healthcare	Biotechnology
118. REGENXBIO Inc.	RGNX	Healthcare	Biotechnology
119. Retrophin, Inc.	RTRX	Healthcare	Drug Manufacturers - Major
120. Revance Therapeutics, Inc.	RVNC	Healthcare	Biotechnology
121. Rhythm Pharmaceuticals, Inc.	RYTM	Healthcare	Biotechnology
122. Sage Therapeutics, Inc.	SAGE	Healthcare	Biotechnology
123. Strongbridge Biopharma plc	SBBP	Healthcare	Biotechnology
124. Seattle Genetics, Inc.	SGEN	Healthcare	Biotechnology
125. Syndax Pharmaceuticals, Inc.	SNDX	Healthcare	Biotechnology
126. Soligenix, Inc.	SNGX	Healthcare	Biotechnology
127. Sophiris Bio, Inc.	SPHS	Healthcare	Biotechnology
128. Spectrum Pharmaceuticals, Inc.	SPPI	Healthcare	Biotechnology
129. Sarepta Therapeutics, Inc.	SRPT	Healthcare	Biotechnology
130. Supernus Pharmaceuticals, Inc.	SUPN	Healthcare	Drug Manufacturers - Major
131. Savara Inc.	SVRA	Healthcare	Biotechnology
132. Theravance Biopharma, Inc.	TBPH	Healthcare	Biotechnology
133. TRACON Pharmaceuticals, Inc.	TCON	Healthcare	Biotechnology
134. TG Therapeutics, Inc.	TGTX	Healthcare	Biotechnology
135. Tonix Pharmaceuticals Holding Corp.	TNXP	Healthcare	Biotechnology
136. Tocagen Inc.	TOCA	Healthcare	Biotechnology
137. Tesaro, Inc.	TSRO	Healthcare	Biotechnology
138. Tetraphase Pharmaceuticals, Inc.	TTPH	Healthcare	Biotechnology
139. UroGen Pharma Ltd.	URGN	Healthcare	Biotechnology
140. United Therapeutics Corporation	UTHR	Healthcare	Biotechnology
141. Vascular Biogenics Ltd.	VBLT	Healthcare	Biotechnology
142. Vertex Pharmaceuticals Incorporated	VRTX	Healthcare	Biotechnology
143. Versartis, Inc.	VSAR	Healthcare	Biotechnology
144. Verastem, Inc.	VSTM	Healthcare	Biotechnology
145. Vital Therapies, Inc.	VTL	Healthcare	Biotechnology
146. vTv Therapeutics Inc.	VTVT	Healthcare	Biotechnology
147. XBiotech Inc.	XBIT	Healthcare	Biotechnology
148. Acceleron Pharma Inc.	XLRN	Healthcare	Biotechnology
149. Xencor, Inc.	XNCR	Healthcare	Biotechnology
150. Zogenix, Inc.	ZGNX	Healthcare	Drug Manufacturers - Major

Table 8: Part 1 - Final Sample of Companies

Company	Ticker	Sector	Industry
1. ACADIA Pharmaceuticals Inc.	ACAD	Healthcare	Biotechnology
2. Achieve Life Sciences, Inc.	ACHV	Healthcare	Biotechnology
3. AC Immune SA	ACIU	Healthcare	Biotechnology
4. Advaxis, Inc.	ADXS	Healthcare	Biotechnology
5. Agios Pharmaceuticals, Inc.	AGIO	Healthcare	Biotechnology
6. Aimmune Therapeutics, Inc.	AIMT	Healthcare	Biotechnology
7. Akebia Therapeutics, Inc.	AKBA	Healthcare	Biotechnology
8. Akcea Therapeutics, Inc.	AKCA	Healthcare	Biotechnology
9. Albireo Pharma, Inc.	ALBO	Healthcare	Biotechnology
10. Alder Biopharmaceuticals, Inc.	ALDR	Healthcare	Biotechnology
11. Alkermes plc	ALKS	Healthcare	Biotechnology
12. Alnylam Pharmaceuticals, Inc.	ALNY	Healthcare	Biotechnology
13. Alexion Pharmaceuticals, Inc.	ALXN	Healthcare	Biotechnology
14. AMAG Pharmaceuticals, Inc.	AMAG	Healthcare	Biotechnology
15. Amgen Inc.	AMGN	Healthcare	Biotechnology
16. Anthera Pharmaceuticals, Inc.	ANTH	Healthcare	Biotechnology
17. Ardelyx, Inc.	ARDX	Healthcare	Biotechnology
18. Arena Pharmaceuticals, Inc.	ARNA	Healthcare	Biotechnology
19. ArQule, Inc.	ARQL	Healthcare	Biotechnology
20. Array BioPharma Inc.	ARRY	Healthcare	Biotechnology
21. Atara Biotherapeutics, Inc.	ATRA	Healthcare	Biotechnology
22. Avadel Pharmaceuticals plc	AVDL	Healthcare	Biotechnology
23. AVEO Pharmaceuticals, Inc.	AVEO	Healthcare	Biotechnology
24. Axovant Sciences Ltd.	AXON	Healthcare	Biotechnology
25. Axsome Therapeutics, Inc.	AXSM	Healthcare	Biotechnology
26. BioCryst Pharmaceuticals, Inc.	BCRX	Healthcare	Biotechnology
27. BeiGene, Ltd.	BGNE	Healthcare	Biotechnology
28. Biogen Inc.	BIIB	Healthcare	Biotechnology
29. bluebird bio, Inc.	BLUE	Healthcare	Biotechnology
30. BioMarin Pharmaceutical Inc.	BMRN	Healthcare	Biotechnology
31. Blueprint Medicines Corporation	BPMC	Healthcare	Biotechnology
32. Cara Therapeutics, Inc.	CARA	Healthcare	Biotechnology
33. China Biologic Products Holdings, Inc.	CBPO	Healthcare	Biotechnology
34. ChemoCentryx, Inc.	CCXI	Healthcare	Biotechnology
35. Celgene Corporation	CELG	Healthcare	Biotechnology
36. Cerus Corporation	CERS	Healthcare	Biotechnology
37. Coherus BioSciences, Inc.	CHRS	Healthcare	Biotechnology
38. Clearside Biomedical, Inc.	CLSD	Healthcare	Biotechnology
39. Clovis Oncology, Inc.	CLVS	Healthcare	Biotechnology
40. Clementia Pharmaceuticals Inc.	CMTA	Healthcare	Biotechnology
41. Concert Pharmaceuticals, Inc.	CNCE	Healthcare	Biotechnology
42. Corbus Pharmaceuticals Holdings, Inc.	CRBP	Healthcare	Biotechnology

Table 9: Part 2 - Final Sample of Companies

Company	Ticker	Sector	Industry
43. CTI BioPharma Corp.	CTIC	Healthcare	Biotechnology
44. ContraVir Pharmaceuticals, Inc.	CTRV	Healthcare	Biotechnology
45. Cytokinetics, Incorporated	CYTK	Healthcare	Biotechnology
46. CytRx Corporation	CYTR	Healthcare	Biotechnology
47. Dermira, Inc.	DERM	Healthcare	Biotechnology
48. DelMar Pharmaceuticals, Inc.	DMPI	Healthcare	Biotechnology
49. Dova Pharmaceuticals, Inc.	DOVA	Healthcare	Biotechnology
50. Auris Medical Holding AG	EARS	Healthcare	Biotechnology
51. Edge Therapeutics, Inc.	EDGE	Healthcare	Biotechnology
52. Egalet Corporation	EGLT	Healthcare	Biotechnology
53. Exelixis, Inc.	EXEL	Healthcare	Biotechnology
54. EyeGate Pharmaceuticals, Inc.	EYEG	Healthcare	Biotechnology
55. Amicus Therapeutics, Inc.	FOLD	Healthcare	Biotechnology
56. Global Blood Therapeutics, Inc.	GBT	Healthcare	Biotechnology
57. Geron Corporation	GERN	Healthcare	Biotechnology
58. Gilead Sciences, Inc.	GILD	Healthcare	Biotechnology
59. GlycoMimetics, Inc.	GLYC	Healthcare	Biotechnology
60. Genocea Biosciences, Inc.	GNCA	Healthcare	Biotechnology
61. Halozyme Therapeutics, Inc.	HALO	Healthcare	Biotechnology
62. Histogenics Corporation	HSGX	Healthcare	Biotechnology
63. Intercept Pharmaceuticals, Inc.	ICPT	Healthcare	Biotechnology
64. ImmunoGen, Inc.	IMGN	Healthcare	Biotechnology
65. Immunomedics, Inc.	IMMU	Healthcare	Biotechnology
66. Incyte Corporation	INCY	Healthcare	Biotechnology
67. Inovio Pharmaceuticals, Inc.	INO	Healthcare	Biotechnology
68. Insmed Incorporated	INSM	Healthcare	Biotechnology
69. INSYS Therapeutics, Inc.	INSY	Healthcare	Biotechnology
70. Ionis Pharmaceuticals, Inc.	IONS	Healthcare	Biotechnology
71. Intra-Cellular Therapies, Inc.	ITCI	Healthcare	Biotechnology
72. Jazz Pharmaceuticals plc	JAZZ	Healthcare	Biotechnology
73. Ligand Pharmaceuticals Incorporated	LGND	Healthcare	Biotechnology
74. Lexicon Pharmaceuticals, Inc.	LXRX	Healthcare	Biotechnology
75. Seres Therapeutics, Inc.	MCRB	Healthcare	Biotechnology
76. MediWound Ltd.	MDWD	Healthcare	Biotechnology
77. MacroGenics, Inc.	MGNX	Healthcare	Biotechnology
78. Melinta Therapeutics, Inc.	MLNT	Healthcare	Biotechnology
79. Neurocrine Biosciences, Inc.	NBIX	Healthcare	Biotechnology
80. NuCana plc	NCNA	Healthcare	Biotechnology
81. Minerva Neurosciences, Inc.	NERV	Healthcare	Biotechnology
82. Nektar Therapeutics	NKTR	Healthcare	Biotechnology
83. NewLink Genetics Corporation	NLNK	Healthcare	Biotechnology
84. Novavax, Inc.	NVAX	Healthcare	Biotechnology
85. ObsEva SA	OBSV	Healthcare	Biotechnology
86. Ocular Therapeutix, Inc.	OCUL	Healthcare	Biotechnology

Table 10: Part 3 - Final Sample of Companies

Company	Ticker	Sector	Industry
87. OHR Pharmaceutical, Inc.	OHRP	Healthcare	Biotechnology
88. Omeros Corporation	OMER	Healthcare	Biotechnology
89. Onconova Therapeutics, Inc.	ONTX	Healthcare	Biotechnology
90. Otonomy, Inc.	OTIC	Healthcare	Biotechnology
91. Puma Biotechnology, Inc.	PBYI	Healthcare	Biotechnology
92. Progenics Pharmaceuticals, Inc.	PGNX	Healthcare	Biotechnology
93. Prothena Corporation plc	PRTA	Healthcare	Biotechnology
94. Proteon Therapeutics, Inc.	PRTO	Healthcare	Biotechnology
95. Proteostasis Therapeutics, Inc.	PTI	Healthcare	Biotechnology
96. Ultragenyx Pharmaceutical Inc.	RARE	Healthcare	Biotechnology
97. Regeneron Pharmaceuticals, Inc.	REGN	Healthcare	Biotechnology
98. Reata Pharmaceuticals, Inc.	RETA	Healthcare	Biotechnology
99. REGENXBIO Inc.	RGNX	Healthcare	Biotechnology
100. Revance Therapeutics, Inc.	RVNC	Healthcare	Biotechnology
101. Rhythm Pharmaceuticals, Inc.	RYTM	Healthcare	Biotechnology
102. Sage Therapeutics, Inc.	SAGE	Healthcare	Biotechnology
103. Strongbridge Biopharma plc	SBBP	Healthcare	Biotechnology
104. Seattle Genetics, Inc.	SGEN	Healthcare	Biotechnology
105. Syndax Pharmaceuticals, Inc.	SNDX	Healthcare	Biotechnology
106. Soligenix, Inc.	SNGX	Healthcare	Biotechnology
107. Sophiris Bio, Inc.	SPHS	Healthcare	Biotechnology
108. Spectrum Pharmaceuticals, Inc.	SPPI	Healthcare	Biotechnology
109. Sarepta Therapeutics, Inc.	SRPT	Healthcare	Biotechnology
110. Savara Inc.	SVRA	Healthcare	Biotechnology
111. Theravance Biopharma, Inc.	TBPH	Healthcare	Biotechnology
112. TRACON Pharmaceuticals, Inc.	TCON	Healthcare	Biotechnology
113. TG Therapeutics, Inc.	TGTX	Healthcare	Biotechnology
114. Tonix Pharmaceuticals Holding Corp.	TNXP	Healthcare	Biotechnology
115. Tocagen Inc.	TOCA	Healthcare	Biotechnology
116. Tesaro, Inc.	TSRO	Healthcare	Biotechnology
117. Tetraphase Pharmaceuticals, Inc.	TTPH	Healthcare	Biotechnology
118. UroGen Pharma Ltd.	URGN	Healthcare	Biotechnology
118. 119. United Therapeutics Corporation	UTHR	Healthcare	Biotechnology
120. Vascular Biogenics Ltd.	VBLT	Healthcare	Biotechnology
121. Vertex Pharmaceuticals Incorporated	VRTX	Healthcare	Biotechnology
122. Versartis, Inc.	VSAR	Healthcare	Biotechnology
123. Verastem, Inc.	VSTM	Healthcare	Biotechnology
124. Vital Therapies, Inc.	VTL	Healthcare	Biotechnology
125. vTv Therapeutics Inc.	VTVT	Healthcare	Biotechnology
126. XBiotech Inc.	XBIT	Healthcare	Biotechnology
127. Acceleron Pharma Inc.	XLRN	Healthcare	Biotechnology
128. Xencor, Inc.	XNCR	Healthcare	Biotechnology

Table 11: Fisher-ADF Panel Unit Root Test

Variable	Tests		Statistic	p-value
MaturityMeasure	Inverse chi-squared(256)	P	1613.4222	0.0000
	Inverse normal	Z	-18.3589	0.0000
	Inverse logit t(644)	L*	-35.2731	0.0000
	Modified inv. chi-squared	Pm	59.9902	0.0000
Earnings	Inverse chi-squared(234)	P	2115.7328	0.0000
	Inverse normal	Z	-27.1931	0.0000
	Inverse logit t(559)	L*	-53.2746	0.0000
	Modified inv. chi-squared	Pm	86.9831	0.0000
Leverage	Inverse chi-squared(236)	P	1484.2746	0.0000
	Inverse normal	Z	-17.1835	0.0000
	Inverse logit t(559)	L*	-34.7303	0.0000
	Modified inv. chi-squared	Pm	57.4565	0.0000
Size	Inverse chi-squared(236)	P	1551.8336	0.0000
	Inverse normal	Z	-16.0882	0.0000
	Inverse logit t(559)	L*	-35.6037	0.0000
	Modified inv. chi-squared	Pm	60.5661	0.0000
RORC	Inverse chi-squared(226)	P	968.5445	0.0000
	Inverse normal	Z	-14.3706	0.0000
	Inverse logit t(434)	L*	-25.8346	0.0000
	Modified inv. chi-squared	Pm	34.9264	0.0000
PEG	Inverse chi-squared(228)	P	903.4837	0.0000
	Inverse normal	Z	-14.3441	0.0000
	Inverse logit t(509)	L*	-21.9326	0.0000
	Modified inv. chi-squared	Pm	31.6324	0.0000
QuickR	Inverse chi-squared(236)	P	1132.3637	0.0000
	Inverse normal	Z	-14.7153	0.0000
	Inverse logit t(554)	L*	-26.5864	0.0000
	Modified inv. chi-squared	Pm	41.2585	0.0000
Nrproductsapproved	Inverse chi-squared(256)	P	1938.5166	0.0000
	Inverse normal	Z	-30.0390	0.0000
	Inverse logit t(644)	L*	-46.8399	0.0000
	Modified inv. chi-squared	Pm	74.3574	0.0000
NrproductsinR&D	Inverse chi-squared(256)	P	911.9241	0.0000
	Inverse normal	Z	-14.4922	0.0000
	Inverse logit t(644)	L*	-20.6764	0.0000
	Modified inv. chi-squared	Pm	28.9880	0.0000

Table 12: The Variance Inflation Factors (VIF)

Variable	VIF
MaturityMeasure	1.75
Earnings	2.07
Leverage	1.56
Size	2.49
RORC	1.15
PEG	1.02
QuickR	1.15
Nrproductsapproved	1.45
NrproductsinR&D	1.04

Table 13: Test Results for Fixed/Random effects, Heteroskedasticity and Autocorrelation

Test	p-value
Hausman specification test	0.0000
Modified Wald test	0.0000
Wooldridge test	0.0153

Table 14: Regression Output MaturityMeasure

This table presents the coefficients of MaturityMeasure, before control variables are added. Stock return volatility (Volatility) is the dependent variable and the independent variable MaturityMeasure is lagged one year. Model (1) exclude period- and industry fixed effects. Model (2) contain period fixed effects. Model (3) contain industry fixed effects. Model (4) contain period- and industry fixed effects. All models are regressed with robust standard errors.

	(1)	(2)	(3)	(4)
Variables	Volatility	Volatility	Volatility	Volatility
MaturityMeasure	-0.005***	-0.005***	0.001	0.002
	(0.00)	(0.00)	(0.00)	(0.00)
Earnings				
Leverage				
Size				
RORC				
PEG				
QuickR				
Nrproductsapproved				
NrproductsinR&D				
Constant	0.807***	1.075***	0.730***	1.029***
	(0.03)	(0.10)	(0.02)	(0.06)
Period fixed	No	Yes	No	Yes
Firm fixed	No	No	Yes	Yes
N	732	732	732	732
R^2	0.023	0.049	0.001	0.044

Robust standard errors in parentheses
* p<0.10, ** p<0.05, *** p<0.01