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Initial Public Offerings

IPO Performance and Prospectus Sentiment of Biotechnology Offerings

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Abstract

This thesis investigates initial public offerings (IPOs) at the Nasdaq exchange in the United States during the time period of 2003 – November 17th, 2017. The focus of the thesis will be on the performance, both in the short- and long-run, of companies in the biotechnology industry. Textual analysis will be applied to determine the effect of prospectus sentiment on performance.

From our sample of 781 observations, we find an average market-adjusted underpricing of 16.6%. The average market-adjusted underpricing is higher in the biotechnology industry relative to other offerings, but this difference is not statistically significant. For the long-run performance, the offerings in our sample perform 1.6 percentage points better relative to the market. The difference between biotechnology and non-biotechnology is not significant.

Our analysis of the IPO prospectuses finds that the companies in the lowest quartile in terms of polarity score of the prospectus summary have less underpricing. Offerings in this quartile perform better in the long-run, while companies in the lower quartile of the risk factors section perform worse.

Preface

This thesis is written as a part of our Master of Science in Financial Economics at the Norwegian School of Economics.

We would like to thank our supervisor, Tore Leite for his support, guidance and thorough feedback of our thesis. We would also like to thank the Norwegian School of Economics and the department of Finance for creating an extensive and interesting Master of Science program.

Contents

1. Introduction

This thesis examines the short- and long-run performance of initial public offerings (IPOs) in the 15-year period of 2003- November 17th, 2017 at the Nasdaq stock exchange. The main focus will lie on the performance of biotechnology companies within the subgroup of medical, biomedical and genetics companies without commercialized products at the time of going public. The effects of issuer sentiment in the prospectuses on IPO performance are also investigated.

There has been extensive research conducted on IPO performance, but to our knowledge there has not been a thesis from NHH that focuses on the performance of biotechnology offerings. As described in section 2.1, biotechnology companies in our sample have a high probability of failure and are often binary of nature. The biotechnology companies in our sample are in the development phases of a product, and are unable to guarantee FDA approval for commercialization. Beatty & Ritter (1986) found that larger ex ante uncertainty leads to a higher level of underpricing. As biotechnology are perceived to have greater ex ante uncertainty, this thesis aims to investigate possible differences in IPO performance relative to non-biotechnology companies.

While empirical studies have examined the effects of market- and investor sentiment, little attention has been devoted to the effect of issuer sentiment on IPO performance as conveyed through the IPO prospectus. This is perhaps due to that the fact that it is a relatively new field of study and is rather complicated to do without programming knowledge. Sentiment can be seen as an issuers attitude towards its own offering. Companies are legally obliged to disclose information about the past, current and future operations of the company. Analyzing the entire prospectus is not as useful as narrowing it down to the most firm-specific sections of the prospectus. Therefore, the sentiment analysis will be performed on the following sections: Prospectus summary, risk factors, and the section for management´s discussion and analysis of financial condition and results of operations.

Based on 781 observations over a 15-year time frame, we find an average market-adjusted underpricing of IPOs at Nasdaq of 16.6%. Biotechnology companies in our sample have a higher, although not significant, average market-adjusted underpricing of 17.7% relative to 16.4% for non-biotechnology companies. Further analysis that control for more variables do

not indicate that companies in the biotechnology industry have a higher abnormal return in the short-run.

IPOs outperform the market by 1.6 percentage points on average in the long-run. However, it is not significantly positive and the majority of our sample performs worse than the market. Biotechnology companies have a lower market-adjusted long-run return with an average return of 0.25%, compared to 1.75% for non-biotechnology companies. The difference is not significant and further analysis through multivariate regressions do not provide evidence of a significant difference in the performance of biotechnology companies.

We do not find a more negative issuer sentiment for biotechnology offerings relative to non-biotechnology offerings. Moreover, we are unable to draw clear conclusions on the effect of issuer sentiment. However, we do find that offerings in the lowest quartile for the polarity of the prospectus summary section have less underpricing and better long-run performance. Companies in the corresponding quartile for the section of risk factors perform worse in the long-run.

2. Literature review

2.1 Biotechnology

Broadly defined, biotechnology *"[...] is technology based on biology – biotechnology harnesses cellular and biomolecular processes to develop technologies and products that help improve our lives and the health of our planet"* (Bio, n.d). The specter of biotechnology is broad and includes, for instance, the somewhat mundane such as processes of preserving dairy products, to the more challenging medical and pharmaceutical application of biotechnology. Our attention will lie on the latter, more specifically the part of biotechnology that falls under the classification of medical, biomedical and genetics biotechnology.

Developing a drug is a process that is both expensive and time-consuming (DiMasi, Grabowski, & Hansen, 2003). The process is also monitored by governmental agencies such as FDA in the US and EMA in Europe. This is done in order to protect consumers and ensure product quality. On average, it takes 10-15 years for a drug to go from initial discovery to clinical approval[1]. Further, when incorporating for the costs of failed compounds, the cost of successfully developing a drug averages to $2.6 billion (PhRMA,2015). Given the tedious and expensive process of drug development, it is even more discouraging that the probability of clinical approval is only 12% (PhRMA, 2015).

The process of developing a drug is traditionally done in five steps (FDA, 2018). First, researchers discover ideas for new or improved drugs through more knowledge of diseases and shortcomings of existing treatments. Following, they must find numerous compounds[2] that have positive effects on the disease they aim to treat. After finding suitable compounds, testing must be done in order to find a candidate drug with which they can proceed. The second step is the preclinical research in which researchers are required to document detailed information of whether the drug has the potential to cause serious harm to people, often called toxicity. Testing is conducted on animals and in the laboratory.

[1] See, among others: DiMasi et al. (2003) and PhRMA (2015)

[2] Compounds are chemicals that could have therapeutic application (Picardo, 2018)

If there is sufficient documentation that dosages and toxicity are manageable, the company can proceed to the third step, which is clinical research. This step consists of three clinical phases, and the aim is to discover how the drug affects the human body. During the first phase, healthy volunteers are recruited, and the researchers scale drug dosages based on the data collected from prior steps. Acute side effects and the drug´s effect on the bodies of volunteers are closely monitored. Through the first phase, researchers must document effects of increased dosage and plan the best administration of the drug such that risks can be limited and benefits enhanced. Phase 2 is somewhat of an extension of phase 1, but with a larger test group. Hundreds of patients with the diagnosis that the drug is intended for are recruited and the agenda is to further document safety regards.

If given the permission to proceed through to Phase 3, the aim is to discover possible side effects that were not present or detected in Phase 2. As this phase can take up to four years, there is a greater chance of documenting longer-run side effects. There is also a Phase 4 clinical trial, but it is conducted only after the drug has received drug approval with the purpose of post-market safety monitoring. Given that a drug has survived all three phases and preclinical research, the firm can file an NDA – New Drug Application. All evidence from prior testing must be documented, and a team from the FDA is assigned to review the application. If the drug is deemed safe and effective for its purpose, and that the benefits are greater than the potential toxicity, the application is approved. Nevertheless, there could still be remaining fallacies that must be sorted out before the drug can be commercialized. In this case, the FDA could require further studies. If the drug finally receives permission to enter the marketplace, it is still monitored by the FDA. Reported problems such as unprecedented side effects are closely reviewed, and the FDA is at liberty to implement a variety of measures, including pulling the drug off the market. Following is table 1, showing the development process of a new drug with estimated time frames, compound developments, and success rates.

Process	Purpose	Time frame	Compound development
Discovery & Research	• Identify potential compounds • Testing compounds	~ 6 years (Discovery and Pre-Clinical combined	5.000-10.000 compounds
Pre-Clinical	• Testing candidate drug in a laboratory and on animals • Document information on dosing and toxicity • Decide whether it should be tested on people		250 compounds
Clinical Phase 1	• Safety and dosage	Several months – 2 years	5 compounds ~ 70% of drugs move to next phase
Clinical Phase 2	• Efficacy and side effects	~ 2 years	~ 33% of drugs move on to next phase
Clinical Phase 3	• Efficacy and monitoring of adverse reactions	1 – 4 years	~ 25-30% of drugs move on to the next phase
FDA Review	• File NDA • Demonstrate that the drug is effective and safe • FDA decides whether the documentation is complete and satisfactory	~ 18 months	1 drug
Post-market monitoring	• Active surveillance by the FDA • Review unprecedented side effects	Continuously	

Sources: DiMasi et al. (2003), Efrata (2008) and *FDA (2018)*

Table 1 – Development process of a new drug. Details given of the process, purpose, time frame and compound development.

As shown, the process from the discovery stage to an FDA approval is challenging. The outcome for a drug in such a process is binary. The drug either receives approval to move on to the next step, and all the way through to drug commercialization step by step, or it must be shut down. Biotechnology companies that do not have any commercialized drugs, such as those in our sample, often have several products in their pipeline. Thus, if one drug fails, their other drugs might still succeed. Nevertheless, there is no guarantee for success, and there are examples of companies with more than one product in the pipeline that still end up dissolved. Millions of raised funds and a lot of time has been devoted to the project with nothing to show for it (Booth, 2017).

In conclusion, investing in a biotechnology company that is in the development stages of a drug is a risky venture. The outcomes are often binary and there is a lot of uncertainty on whether or not the drug will be approved such that the company and its investors can monetize on the venture.

2.2 Motives for firms going public

The academic literature that exists mainly focuses on IPOs as a tool for the following; the cost of capital control, facilitating for a takeover, strategic moves, allowing a cash out for primary insiders and to fund innovation[3].

Modigliani & Miller (1963) argue that an IPO is favorable when external capital aids in minimizing the cost of capital, and by logic maximizing the value of the company. This must be seen in relation to the pecking order of financing (Myers & Majluf, 1961), a theory that helps companies choose the optimal source of financing. The theory is rooted in the assumption that the cost of financing increases when there are asymmetries of information. Following the Pecking Order Theory, its hierarchy postulates that companies prefer internal financing - mainly through retained earnings, before potentially resorting to external financing through issuing either debt or equity. According to this theory, a company would conduct an IPO as a final resort.

Further, a publicly traded company may use its shares as a form of currency when acquiring a company (Brau, Bill, & Kohers, 2003). This is further reiterated by the fact that companies

[3]See Brau & Fawcett (2006) and Steinbach (2018)

seeking growth through mergers and acquisitions, use IPOs as tools to create a market for cash-financed deals (Celikyurt, Svilir, & Shivdasani, 2010).

Empirical work[4] shows how IPOs may be incentivized by the ability to capture first-mover advantage and broadening of the company´s ownership base. The latter serves as a strategic move to dilute the influence of a relatively large shareholder.

Studies[5] also argue that IPOs may be used in order to facilitate the harvesting of gains for primary insiders and exit strategies for venture capitalists.

Growth companies use an IPO to fund innovation, growth, acquisitions and internalization (Steinbach, 2018). As a growth company, IPOs within biotechnology are primarily done to raise capital for drug development. As aforementioned, biotechnology is a tedious and capital-intensive industry. Apart from a select few who have the necessary financial backing from either private or governmental sources, other companies have to go public in order to finance their research. Further, companies that are in the development stages of a drug, and do not have a commercialized product from which they can monetize, have difficulties raising debt. Therefore, they resort to raising equity by listing on a public market.

2.3 Evidence of IPO underpricing phenomenon

Ever since Reilly & Hatfield (1969) were among the first to document the presence of underpricing, the phenomenon has been continuously researched. Underpricing occurs when the offer price of the IPO is lower than the closing price after the first day of trading (Berk & Demarzo, 2014). In this case, the company conducting the IPO must carry the indirect costs as it entails that they are essentially *leaving money on the table.* This effect was shown by Loughran & Ritter (2002) and amounted to an estimated cost of $27 billion for the issuing companies in the United States in the period of 1990-1998.

Table 2 shows various empirical research on underpricing in the US at different time periods. Loughran & Ritter (2004) documented that the underpricing varies over time, ranging from

[4] See Maksimovic & Pichler (2001) and Chemmanur & Fulghieri (1999)

[5] See Zingales (1995), Ang & Brau (2003) and Black & Gilson (1998)

65% during the dot-com bubble, to 12% in the subsequent 3 years. Moreover, it has been documented that offerings conducted in *hot* markets are significantly higher than offerings during *cold* markets (Ritter, 1984).

The research by Loughran, Ritter & Rydqvist (1994) documents that underpricing varies across countries, ranging from 4,2% in France to 80,3% in Malaysia. Furthermore, underpricing also varies across industries. Ritter (1991) shows how the lowest degree of underpricing occurred in the Wholesale industry averaging 1,42%, and the highest being documented in the Financial Institutions industry with an average of 128,21%.

Authors	**Market**	**Time period**	**Average underpricing**
Reilly & Hatfield, 1969	USA	1963-1966	9.9%
Ibbotson, 1975	USA	1960-1969	11.4%
Ljungqvist & Wilhelm Jr., 2003	USA	1996-2000	35.7%
Loughran & Ritter, 2004	USA	1980-2003	18.7%
Bakke, Leite, & Thorburn, 2010	USA	1981-2008	19.2%

Table 2 – Previous research on IPOs short-run performance. Average underpricing is given by market and time period.

2.4 Theories of short-run IPO performance

Theories seeking to explain why underpricing occurs are ubiquitous, but nevertheless rooted in extensive research. Generally, there are four classes of theories that are spearheading the field.

- Asymmetric information theories that assume discrepancy in the level of information possessed by different parties.
- Theories focusing on institutional explanations, where legal liabilities, taxes and price stabilization are important factors.
- Theories of utilizing underpricing for corporate control purposes.
- Behavioral theories that explore the rationality of investors.

These theories are not mutually exclusive, and can be present at the same time. Following is a short assessment of some of the main theories within each of the four classes, and a brief presentation of their empirical predictors.

2.4.1 Asymmetric Information

Winner´s curse

Rock (1986) presents a model for underpricing of IPOs, which assumes that there exist information asymmetries among the investors of the offering. Generally, we can divide the investors into two groups, where one group is regarded as informed while the other is uninformed. While informed investors can observe the intrinsic value of the firm, uninformed investors lack this information. As the uninformed group cannot decide whether to participate in an IPO on the basis of intrinsic value, they will only purchase shares if the offer price is low enough. On the other hand, informed investors participate if, and only if the offer price is below the intrinsic value. As informed investors leave the offering when the price is higher than the intrinsic value, uninformed investors are allocated a larger portion of the offering. This is the core of the winner´s curse problem. Furthermore, it is assumed that none of the groups have sufficient wealth to subscribe the entirety of the offering alone. As a consequence, the issuing firm must offer the shares at a discount in order to attract the uninformed group such that the offering is fully subscribed. Leite (2007), on the other hand, generalizes the informational environment of Rock (1986) and asserts that investors only differ in the precision of their private information. Leite´s argument goes outside the standard model of information asymmetries and wealth constraints, and finds how positive public information such as positive market returns reduce adverse selection which in turn reduces the winner´s curse problem.

Benveniste & Spindt, (1989) show that underpricing arises in order to entice investors to truthfully reveal their positive information. They also argue that underwriters can use the disclosed information to reduce underpricing. Bakke, Leite, & Thorburn (2017) further expand Benveniste & Spindt´s framework by including public signals. They argue that public information affects underpricing through two mechanisms. First through the higher likelihood of sufficient demand for an issue when there is a positive public signal. The second mechanism is that investors demand more underpricing, which serves as compensation, in order to reveal their private information when there is a negative public signal.

Empirical predictions related to the matter of asymmetric information assert that while informed investors only profit to the point of covering the cost of being informed, the uninformed investors earn zero initial returns (Ljungqvist, 2007). However, there lies no

evidence on the costs of becoming informed. Aggarwal, Prabhala & Puri (2002) suggest that it is difficult to verify who is informed and not, but they find evidence that large, institutional investors have a tendency of receiving a greater allocation of shares for the most underpriced IPOs.

Principal-agent problems

While an important role of underwriters is to elicit information that aids in setting the IPO price, Loughran & Ritter (2004) show how arrangements between the issuing firm and underwriters may lead to disalignments in the parties´ interests and rent-seeking behavior. As investors can benefit by being allocated underpriced shares, rent-seeking behavior can arise when these investors offer the underwriter an incentive to allocate the shares in their favor. Such incentives are commonly in the form of well-hid side-payments to the underwriter (Ljungqvist, 2004). Behaving in this manner increases the underwriter´s wealth without creating additional wealth to society. Another approach for underwriters to benefit from purposely underpricing an IPO is to *spin* or allocate underpriced shares to executives of whom they hope to attract future business from. These are mainly large institutional investors.

Ljungqvist & Wilhelm (2002) empirically show how aligning the interests of the CEO and the underwriter, decreases underpricing. Reuter (2004) on the other hand documents how institutional investors are being allocated underpriced IPOs. This is done by using post-IPO reported holdings and matching them against commisions paid to lead managers of the IPO. The paper shows a positive relationship between the amount of commisions paid and the size of their holdings. Thus, both the principle-agent problem and the occurrence of rent-seeking behavior are empirically predicted.

Signaling theory

Several researchers[6] assert that issuing firms can use underpricing as a tool to signal that its prospects for the future are positive. Their results rest on the assumptions that the issuing firm knows their future potential best and that investors believe only the most promising firms have the luxury of signaling by underpricing. By extension, firms with poor prospects should not - and can not afford to underprice. Moreover, firms signaling such notions, want to *leave a good*

[6] See, among others: Grinblatt & Hwang (1989), Allen & Faulhaber (1989) and Welch (1989)

taste in the mouth to entice investors because they might want to issue equity at more favorable terms later on (Ibbotson, 1975).

However, the use of underpricing for signaling quality of the firm is under great scrutiny empirically. In addition to underpricing, theory suggests several other ways of signaling the quality of the firm. Among those are retaining a substantial part of the offered shares, or hiring top-tier underwriters. The former signal suggests that the primary insiders, who know the firm best, have such positive beliefs for the future that they are not willing to sell their shares. Nevertheless, empirical evidence for the signaling efforts baring economic gains are rather weak. Spiess & Pettway (1997) discard the hypothesis that firms are able to recoup the cost of underpricing. They also show how there is no significant difference in how many shares insiders sell in later offerings.

2.4.2 Institutional explanations

Legal liability

A central theme for institutional explanations of underpricing is the lawsuit avoidance hypothesis of Tiniç (1998). The logic behind it is that firms intentionally underprice their offers in order to avoid litigations by disgruntled shareholders who are not satisfied with their stock´s performance. As IPO prospectuses in the U.S are regulated stringently, disputes embedded in the content of the prospectus can often lead to litigations. For this reason, the lawsuit avoidance hypothesis is most prominently studied in the U.S[7].

The empirical evidence on the matter is, however, ambiguous. On the one hand, Lowry & Shu (2002) posit that underpricing may be used as insurance against litigation, and that greater underpricing lowers expected costs of litigations. Drake & Vetsuypens (1993), on the other hand, find no significant evidence of this. Lowry & Shu (2002), find that 5.8% of firms with IPOs in the period between 1988 to 1995, faced litigations for violations in IPO documents. On average, the settlements amounted to 10.1% of the proceeds raised in the IPO. There is a great body of literature devoted to the matter, and the consensus is that legal liabilities have a second-order effect on underpricing at best.

[7] See Tiniç (1998) and Lowry & Shu (2002).

Tax arguments

Theories that seek to explain underpricing on a tax basis, assume that capital gains are taxed more favorably than employment income. When this is the case, an incentive to initiate an employee stock ownership program (ESOP) occurs. Employees are better off by holding an underpriced stock that would appreciate, rather than being paid full salaries as income.

Rydqvist (1997) concluded that tax arguments could aid in explaining underpricing. The practice of allocating underpriced shares to employees serves as a tax-efficient compensation, and is the basis of Rydqvist´s findings. Prior to 1990, capital gains were taxed at a lower rate than employment income in Sweden. Thus, the aforementioned tax-efficient incentive of ESOPs was present. In 1990, however, Swedish regulators removed this incentive by taxing income and capital gains derived from underpricing at the same rate. As a result, the average underpricing fell from 41% in 1980 to 1980, to 8% in the following 4 years. Further, Taranto (2003) finds empirical support for greater underpricing in firms with extensive use of ESOPs. He also shows how stock options explain a lot of the variation in IPO underpricing.

2.4.3 Ownership and corporate control

Going public often changes the ownership base of a company substantially. As a result, two conflicting objectives for underpricing arise. While some research claims that underpricing is used in order to avoid external monitoring, others claim underpricing is done to encourage exactly that. By creating excess demand for an IPO, underpricing facilitates for a dispersion of the firm´s ownership base. Thus, the firm avoids allocating a large bulk of shares to a small group of investors, who could then obtain corporate control.

Brennan & Franks (1997) argue that managers are incentivized to underprice in order to retain corporate control by allocating shares to many, small and passive shareholders. In the seven years following an IPO, they find that management sell very little of their shares. In comparison, other insiders sell of nearly the entirety of their holdings in the same period. Consequently, management are able to retain control and avoid being subjected to external monitoring. Stoughton & Zechner (1998) on the other hand, assert that managers with large bulks of shares bear great costs of entrenching control. They argue that these managers should aim to reduce these costs. Further, they observe incentives to allocate large bulks of shares to large investors who are capable of exercising monitoring. Underpricing aids in enticing such investors. Their

research is based on the logic that underpricing is not a direct cost, but is done in hopes of appreciating stock price from positive expectations of monitoring.

2.4.4 Behavioral theories

Information cascades

Information cascades can be compared to conforming to group mentality, where decisions are made on the basis of what has been done earlier. Milgram, Bickman & Berkowitz (1969) conducted an experiment where they tested the drawing power of crowds. An inference of the results is that people follow crowds in their quest for social conformity. Such behavior can be seen in some forms of IPOs. Welch (1992) argues how potential investors learn from the decisions of earlier investors and mimic their actions while disregarding their own information. However, this only applies when shares are sold sequentially in an IPO process.

Welch (1992) shows how subsequent investors interpret successful initial sales as an indication of initial investors having had positive information. By this interpretation, subsequent investors are encouraged to mimic the actions of initial investors. In contrast, if initial sales are weak, subsequent investors are discouraged from investing, regardless of what their private information may dictate. Information cascades thus lead to somewhat binary outcomes of an IPO, where the demand for the IPO shares either compounds substantially, or remains low. An implication of information cascades is that they could facilitate for market power to initial investors who may demand underpricing in order to set off positive cascades. These effects are driven by the restriction of free communication between investors, and if no such restrictions are imposed, cascades would not have any breeding ground. Nevertheless, Welch (1992) asserts that cascades, in fact, are more favorable than free communication for issuers. The argument is that "*free communication aggregates all available information which maximizes the issuing company´s informational disadvantage compared to investors*" Ljungqvist (2004).

2.5 Evidence of long-run IPO performance

While underpricing has been extensively researched, there is less empirical work on the long-run performance of IPOs. However, the research addressing long-run performance often concludes that the IPOs underperform. Ritter (1991), for instance, shows how investors who

would have invested in a firm at their post-market equilibrium price, would on average occur losses of 17% relative to investing in matching peers on the American and New York stock exchanges.

As is the case of underpricing, long-run performance also varies by country, time periods, and industry as well (Ritter, 1991). He also highlighted that the underperfermance of his sample was primarily found in the final two years of his selected time-frame. Previous research on long-term performance is listed in table 3.

Authors	Market	Time period	Average performance	Time-frame
Ritter J., 1991	USA	1975-1984	-29.13%	3 Years
Loughran, Ritter, & Rydqvist, 1994	Sweden	1980-1990	1.2%	3 Years
Giudici & Roosenboom, 2004	Europe	1996-2000	-32%	3 Years
Aggarwal & Rivoli, Eva, 1991	USA	1977-1987	-13.73%	1 Year
Aggarwal, Leal, & Hernandez, 1993	Brazil	1980-1990	-47%	3 Years
Neneh & Smit, 2014	South Africa	1996-2007	-65.69%	3 Years

Table 3 – Previous research on IPO long-run performance. Average performance by market, time period and time-frame of the research.

2.6 Theories of long-run IPO performance

The body of literature offers different explanations for the long-run performance. While Shiller (1990) credits the poor long-run performance to market fads, Miller (1977) argues it is the doing of overoptimistic investors. Ritter (1991), on the other hand, shows how issuers timing *windows of opportunity* that arise from investors overestimating the potential of young growth companies are the root of the cause. Furthermore, Eckbo & Norli (2005) argue that the liquidity (turnover) of stocks has explanatory power.

2.6.1 Market fads

To create greater demand for subsequent IPOs, Shiller (1990) claims that underwriters purposely underprice in order to create an impression of excess demand. He hypothesizes this under *The impresario hypothesis.* Following this hypothesis, Shiller argues underwriters allow high initial returns to keep up with appearances as successful underwriters in the eyes of investors. In line with De Bondt & Thaler´s (1985, 1987) overreaction hypothesis, Shiller also

assumes such market fads. Further, he shows that by market mechanisms, the high initial returns reverse to negative long-run performance as more information is disclosed over time.

2.6.2 Optimism

According to Miller (1977), there is a difference in opinion of the true value of an IPO between optimistic- and pessimistic investors. This is the basis of Miller´s hypothesis *The divergence of opinion* which argues that this divergence of opinion results in the beliefs of optimistic investors dominating. This leads to an initial overvaluation, before a subsequent price adjustment downwards resulting from a decrease in the divergence of opinion over time. The decrease is a consequence of more information being available. Moreover, Miller posits that the divergence is greater as the ex ante uncertainty of the true IPO value increases. Thus, a negative relationship between long-run performance and ex ante uncertainty lies at the core of his research.

2.6.3 Windows of opportunities

This theory argues that managers time their IPOs to periods when the stock market is doing well and there are many IPOs, such that they can take advantage of the optimism existing in the market (Ritter, 1991). Ritter finds that in such high-volume periods, investors have a willingness to pay higher multiples for future growth of the firm. However, when the firm later shows disappointing growth, the IPO underperforms. Bayless & Chaplinsky (1996) point to the same market-timing theories of an existing *window of opportunity* when the cost of equity is low, meaning that equity is overvalued.

2.6.4 Liquidity

Empirical studies[8] argue that liquidity may serve as a proxy for risk and that lower stock liquidity, defined by lower turnover, increases risk. Eckbo & Norli (2005) show that IPO stocks have greater liquidity, and argue when controlling for this, long-run IPO returns do not underperform.

[8] See, among others: Brennan & Subrahmanyama (1996), Pastor & Stambaugh (2003) and Eckbo & Norli (2002)

2.7 Factors influencing IPO performance

Company age

The age of the firm at the time of the IPO has been proven to affect both the initial underpricing and post-IPO performance of a stock[9]. Given that younger companies do not have a proven track record, these companies are riskier (Ritter, 1984). Because of the mentioned qualities, firm age serves well as a proxy for risk, which is in line with Beatty & Ritter (1986). Further, Ritter (1984) argues that informed investors demand a discounted price for young firms as the information collection is costlier. These arguments result in the expectation of lower underpricing in the short run and better long-run performance for an older company.

Additionally, Jovanovic & Rousseau (2001) view the period prior to the IPO as a learning period where lenders and management can refine and develop the firm´s strategy and ideas while assessing potential and risk. They argue that there exists a trade-off between learning about the firm and the opportunity cost of delaying its IPO and that firms aim to maximize the net present value of this trade-off. By logic, the higher the opportunity cost of waiting for the IPO, the earlier the firm will list.

Offer size

Following Beatty & Ritter (1986), there is a clear relationship between the level of underpricing and the size of the offer. The offer size serves as a proxy for risk by the assumption that firms with small offer sizes are smaller firms, and thus more prone to greater ex ante uncertainty. More precisely, they find that the smaller an offer is, the more underpricing one can expect. Their findings indicate higher initial returns for firms with small offer sizes. Ritter (1991) finds that larger firms tend to outperform smaller firms in the long-run.

Underwriter

According to Chemmanur & Fulghieri (1999), investors consider the underwriter´s past performance and reputation as indicators of the listing firm´s quality. On the one hand, the seal of quality provided by having a prestigious investment bank underwriting its IPO, would lead to higher demands. This would, in turn, lead to higher short-run underpricing and positive long-

[9] See, among others: Loughran & Ritter (2004) and Clark (2002)

run returns. However, the majority of existing literature finds evidence of less underpricing in the short-run and argues that prestigious underwriters better certify the true value of the firm.

Nevertheless, there are examples of time periods where the effect of prestigious underwriters has been reversed. Beatty & Welch (1996) find this relationship for the time period 1992-1994. They propose that the reversal of this effect is to be accredited to The Securities Acts of 1933 and 1934, which aims to ensure transparency by allowing investors to rightfully sue IPO firms as a result of omissions or untruthfulness in the prospectus. Lowry & Shu (2002) argue that litigation risk is especially high for companies that are hard to value, such as high-technology companies. The rapid emergence of technology offerings in the 1990s might explain why this dynamic was not observed until several decades after The Securities Acts of 1933 and 1934.

For the long-run performance, the use of a prestigious underwriter leads to better long-run performance relative to offerings from non-prestigious underwriters[10]. An explanation for the long-run performance could be that prestigious underwriters have greater access to issuers. Thus, they have greater opportunity to screen IPO candidates and proceed with the most promising (Dong, Michel, & Pandes, 2011).

Industry

As aforementioned, Ritter (1991) shows how underpricing and long-run performance varies across industries. In line with the argument of increased underpricing with greater ex ante uncertainty, research finds the same relationship in industry-related underpricing and long-run performance. Industries that are riskier by nature, tend to be more underpriced in the short-run than *safer* industries (Bravo, 1998). Apart from the restaurant-, financial institution-, and insurance industry, Bravo finds that IPOs underperform in the long-run. He argues that the future risks of the mentioned industries are more easily quantifiable, thus reducing ex ante uncertainty and underperformance.

VC

There is a broad agreement in the literature that VC-backed IPOs have a less underpricing. The argument is that being backed by venture capitalists serves as a certification that reduces information asymmetry (Megginson & Weiss, 1991). This effect is even stronger if the VC has

[10] See, among others: Booth & Smith (1986), Beatty & Ritter (1986), Maksimovic & Unal (1993) and Michaely & Shaw (1994)

a positive past performance. Further, Brav & Gompers (1997) show how VC-backed IPOs have better long-run performance than their counterparts who are not backed by a VC. They attribute their findings to VC´s demands of better corporate governance and management composition.

Time periods

Empirical studies show that IPO activity varies over time periods (Loughran & Ritter, 2004). Both short- and long-run performance are affected by varying conditions that are present in different time periods. In other words, IPO performance can be affected by possible changes in the market scenery between periods. These changes could be of macroeconomic nature, like the financial crisis of 2007-2008, business cycles, institutional changes and so on.

Pre-listing market return

Leite (2007) asserts that the costs of going public are negatively related to market returns. In his research, Leite proxies high market returns as favorable public information, and shows how this proxy reduces the winner´s curse problem and leads to more conservatively priced IPOs. By extension, this results in a positive relationship between underpricing and market returns, which is also consistent with other empirical research[11]. In other words, IPOs conducted in *bear* markets would be less underpriced than those in *bull* markets. In relation to the *window of opportunities* hypothesis, offering that takes place in *bull* markets might be overpriced. This would thereby lead to a price reversal in the long-run.

Issuer Sentiment

The effects of issuer sentiment, as conveyed through the IPO prospectus of the firm, on IPO short- and long-run performance, are ambiguous in the existing literature. How a given tone of the prospectus relates to the two metrics depends on which beliefs investors subscribe to (Ferris, Hao, & Liao, 2012). On the one hand, if a negative sentiment is viewed as a cautionary approach with many reservations, a negative sentiment could add credibility to the issue. As a result, the pre-IPO demand would increase, which in turn would lead to less needed underpricing. However, a cautious approach could signal that the issuer is not very confident about the future of their business. If so, they run the risk of the issue not being fully subscribed. Therefore, more underpricing might be needed in order to ensure a full subscription. Ferris et al. (2012) address

[11] See, among others, Ritter (1984), Logue (1973) and Amihud, Hauser & Kirsh (2003)

these points and find higher short-run underpricing for offerings with a negative sentiment in the prospectus.

On a separate note, it must also be mentioned that a cautionary approach could be applied in order to lower the risk of litigation by shareholders. Lowry & Shu (2002) argue that issuers deliberately underprice their IPOs as insurance against litigation. By extension, one could make the argument that a cautious prospectus could substitute underpricing as litigation insurance. Hence, one would expect less underpricing in IPOs with a negative sentiment in the prospectus. Arnold, Fishe, & North (2010) find that disclosures in the risk factors section of the prospectus are subject to ambiguous interpretations by the reader, and that the ambiguity is significant in explaining initial underpricing and long-run performance. However, the empirical research on the effects of prospectus sentiment on long-run IPO performance is rather scarce. Nevertheless, Ferris et al. (2012) find a negative relation between the sentiment of the management´s discussion and analysis of financial condition and results of operations (M.D.A) in the prospectus and long-run IPO performance for non-technology firms.

Over the years, the Security and Exchange Commission (SEC) has implemented stricter regulations for disclosure of information in SEC filings. Issuers are obliged to follow stringent layouts of filings and are required to disclose specific details in specific sections (EY, 2016). S-1 filings, in which the firm´s prospectus is included, are under the same requirements. While S-1 filings contain several sections, Hanley & Hoberg (2010) assert that the sections prospectus summary, use of proceeds, M.D.A, and risk factors are the most relevant and firm-specific. This is also in line with EY (2016) who rank the importance of such sections on the basis of review comments made by the SEC. They find risk factors and M.D.A to be ranked first and second respectively. The use of proceeds section is a description of the firm´s intentions with the raised proceeds from the IPO. Risk factors explain the most important factors that the firm is facing and they must be related to the firm´s actual circumstances, and not just generic risks that could apply to anyone. While the prospectus summary is a brief summary of key information in the prospectus, M.D.A addresses factors that may affect future performance. The M.D.A section´s function is to allow the reader to comprehend the likely outcome of future operations[12].

12 See Ferris et al. (2012) and PWC (2017)

2.8 Hypotheses

As discussed, biotechnology stocks in our scope of focus are perceived as risky investments. Approximately 88% of biotechnological drug candidates do not succeed in receiving FDA approval, which in turn does not result in a commercialized product (PhRMA, 2015). In order to fund the drug development process, biotechnology companies must often resort to IPOs, as they are unable to raise sufficient debt given their lack of generating significant revenue. Beatty & Ritter (1986) found that underpricing increases with ex ante uncertainty. Thus, this makes the basis of our first hypothesis:

Hypothesis 1: Biotechnology IPOs will have higher underpricing relative to non-biotechnology IPOs.

Companies going public are required, by the SEC, to disclose detailed information of past, current and future events and firm-specific risk factors related to their operations. Following this, biotechnology firms disclose that their clinical trials may never result in commercialized products and that they currently do not, and might never, generate significant revenue. Our second hypothesis will thereby be as follows:

Hypothesis 2: Biotechnology IPOs will have a more negative sentiment relative to non-biotechnology IPOs.

If an issuer's sentiment is perceived as a realistic expectation of the future, the firm does not have to underprice their offer in order to ensure a full subscription. As mentioned in our literature review, a negative sentiment can be interpreted as either a sign of credibility or the issuer's uncertainty of its operations. We find the former as the most plausible assumption, leading to our hypothesis of:

Hypothesis 3: A prospectus with a more negative sentiment will have less underpricing.

Based on table 1, our chosen time frame of one year reduces the probability of a biotechnology company completing their current development phase. As there will be no fundamental change in the company within one year, our fourth hypothesis will be the following:

Hypothesis 4: Biotechnology companies do not differ in performance compared to non-biotechnology companies in the long-run.

The effect of prospectus sentiment on long-run performance is unclear based on the limited literature we have presented. The time it takes for an efficient market price to be set is an important part of the discussion among researchers to determine the long-run performance. As we discuss in section 3.2.1, we assume that the first closing price has fully incorporated all available market information. This would imply that the long-run effect of prospectus sentiment should not affect the long-run performance of an IPO and leads to our final hypothesis:

Hypothesis 5: The prospectus sentiment should not affect the long-run performance of an IPO.

3. Methodology

The following section will explain the methods used to calculate potential underpricing and long-run performance of IPOs. Firstly, the choice of the market will be explained, before the data collection and sample size will be discussed. This will be followed by an explanation of our variables and regression models, both for the short-run and long-run performance. Finally, possible violations of our regression models will be discussed.

3.1 Data

3.1.1 Choice of the market

The United States is the leading country worldwide for biotechnology, outspending the second country on the list eight-fold in terms of research and development expenditure measured as of 2012 (Bonala, 2016). This thesis' choice of investigating the American market is made to create as large sample size of IPOs as possible.

The Nasdaq exchange created an index for biotechnology stocks in 1993 and has branded itself as the primary exchange for biotechnology (Nasdaq OMX, 2018). Arguably, the motivation for going public is based on raising capital to fund research and development. Traditionally, such companies tend to be younger and smaller as they go public. The Nasdaq index consists of smaller firms compared to a stock exchange like the New York Stock Exchange (NYSE), while also accounting for 7% of the total number of global IPOs as of 2016 (Desjardins, 2017). Nasdaq is thereby determined to be the optimal exchange for our analysis. Furthermore, with more than 3 300 companies enlisted (Nasdaq, 2018), it is determined to serve as a robust benchmark for this thesis.

3.1.2 Data collection

Data is collected from several sources. While the majority of our data is collected from the Bloomberg Financial Terminal, there are some exceptions. S-1 filings are collected from SEC. The incorporation date is mainly collected from Ritter (n.d.), but there were some missing observations that have been collected from Bloomberg. All leading underwriters that are not available from the Bloomberg terminal, were retrieved from the S-1 filings. US inflation figures are collected from the US Bureau of Labor Statistics (Bureau of Labor Statistics, 2018).

3.1.3 Sample size

In order to exclude *penny stocks* from our sample, we only collect IPOs with an offer price of $5 or larger (Hanley & Hoberg, 2010). All IPOs at Nasdaq in the period of 2003-2018 are collected, as well as all delisted IPOs that went public in the same period. This is done to ensure that the survivorship bias is not present (Brown, Goetzmann, Ibbotson, & Ross, 1992). As Bloomberg does not show which exchange was used for delisted companies in the US, these are investigated manually. Initially, 1847 observations consisting of IPOs from Nasdaq or delisted from an exchange in the US are collected. To ensure that the IPOs are comparable, 337 unit offerings are excluded. 438 of the delisted companies went public on other exchanges and are removed. Furthermore, seven IPOs were too recent to calculate returns for the first year and are excluded. As we seek to analyze the biotechnology companies that do not have a commercialized product at the time of going public, the information disclosed in their S-1 filing is inspected. We find three companies that had a commercialized product as they went public and are dropped. We find 80 companies that are required to file their registration in a different form than S-1 because of their classification. Thus, they are removed from our sample for comparability reasons (Arnold, Fishe, & North, 2010).

The textual analysis requires some additional criteria for our dataset. 13 companies are excluded as their filing is saved in *txt-format* as opposed to the needed *html-format*. Further, 188 companies are removed as the table of contents is missing links. Ultimately, the data consists of 781 IPOs, of which 103 are biotechnology companies. The data is presented in figure 1 below.

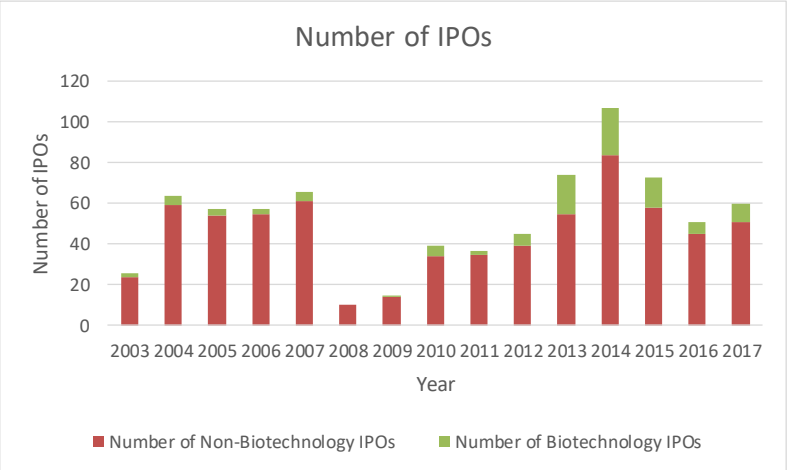

Figure 1 – Number of IPOs by year. Visualized by industry-indicator of biotechnology.

3.2 Regression model

Linear regression and the method of ordinary least squares will be used to determine the relationship between IPO performance and the factors that affect it.

3.2.1 Dependent variable

Various methods have been used to calculate short- and long-run performance. In terms of short-run performance, scholars debate at what point an efficient market price has been set. McGuinness (1992) argues that the price of a stock is efficient after the first day of trading, while others argue that the market needs more time to efficiently price the stock (Lowry, Officer, & Schwert, 2010). In this paper, we will assume that the price is efficient after the first day of trading.

The method of calculating long-run performance also varies. The first closing price will be used as the base to measure long-run performance. This is based on our assumptions of an efficient stock price after the first day of trading. The definition of long-run also varies among researchers where table 3 shows how different time frames ranging from one to three years are commonly practiced. In this thesis, long-run will be defined as one year after the stock has gone through the IPO process in order to limit the possibility of biotechnology companies completing a step in the development phase.

Whether to adjust the returns of the first day of trading with a benchmark or not, also differs among researchers. It can be argued that the changes in the market are relatively small and uncorrelated to the return of the stock in the first trading day (Beatty & Ritter, 1986). On the contrary, the market will affect all stocks which leads to the necessity of adjusting returns by a benchmark (Shi, Pukthuanthong, & Walker, 2012). In this paper, we will adjust initial returns by the return of the Nasdaq index during the first day of trading.

The approach will be similar for the long-run performance of an offering, where the returns will be adjusted by the return of the Nasdaq index for the same time period. This is particularly important as our sample consists of IPOs over a broad time horizon. During our period of 15 years, market conditions will differ and must be adjusted for.

The abnormal return of an IPO in the short- and long-run will be log-transformed to make sure that the results are less skewed and lessen the effect of outliers. This is shown in tables 3-10 in appendix A.

Following is the formula to calculate the short-run abnormal return:

$$AR_{Short-run} = \log\left(\frac{Closing\ Price_{S_1}}{Offer\ Price_S}\right) - \log\left(\frac{Closing\ Price_{m_1}}{Closing\ Price_{m_0}}\right)$$

Where Closing $Price_{S1}$ is the closing price of the stock after one day of trading. Offer $Price_S$ is the offer price of a stock. Closing $Price_{M1}$ is the closing price of the Nasdaq Index after one day of trading, while Closing $Price_{M0}$ is the closing price at time zero, the day before the stock goes public.

Following is the formula to calculate long-run abnormal return:

$$AR_{Long-run} = \log\left(\frac{Closing\ Price_{S_{1\ Year}}}{Closing\ Price_{S_1}}\right) - \log\left(\frac{Closing\ Price_{m_{1\ Year}}}{Closing\ Price_{m_1}}\right)$$

Where Closing $Price_{S1\ Year}$ is the closing price of the stock after one year of trading. Closing $Price_{S1}$ is the closing price after the first day of trading for the stock. Closing $Price_{M1\ Year}$ is the closing price of the Nasdaq Index after one year of trading, while Closing $Price_{M1}$ is the closing price of the Nasdaq Index after the first day of trading for the stock.

3.2.2 Independent variables

The independent variables used in our regressions seek to explain the effect of the factors mentioned in section 2.7 on IPO performance.

Company age

The age of a company at the time of the offering will be measured in line with Ritter (1991). The variable will be log-transformed to ensure linearity. A constant of 1 is added as there exist observations in the dataset that are incorporated in the same year as the public offering.

$$Company\ Age = \log\left(1 + (Year_{IPO} - Year_{Incorporation})\right)$$

Offer Size

The offer size of an IPO is the number of shares offered multiplied by the offer price. As the data is collected for 15 years, the offer size will be adjusted by US inflation to ensure that the value is comparable over the years. The variable will be log-transformed. Note that the variable is given in millions.

$$ADJ\ Offer\ Size = \log\left(Offer\ Size * \frac{CPI_{2017}}{CPI_{Year\ of\ IPO}}\right)$$

Underwriter

The classification of underwriters is based on the ranking of Ritter (2016). The variable is a dummy variable equal to one if the IPO has made use of an underwriter with a top score in the year of the IPO. The latest ranking available is used for the companies gone public in the years after 2014.

Biotechnology

This industry-specific variable will be a dummy variable equal to one if the IPO is a company in the industry of biotechnology. The variable is based on the classification of Bloomberg which includes medical, biomedical and genetics companies.

Venture Capital

Based on the data from Bloomberg, a dummy variable is created for companies backed by venture capital. The independent variable has a value of 1 if the company has been backed by venture capital, zero otherwise.

Time Periods

Time periods are created for the periods 2003-2008, 2008-2010, 2010-2014, while 2014-2018 will be used as the base year. These variables are created as dummy variables, and are meant to capture differences in the market conditions, as the observations are distributed over a 15 year period. The time periods capture the years leading up to the financial crisis of 2008, the financial crisis itself and the years following the economic downturn. The base period of the time period also distinguishes itself after the financial crisis as a period with a relatively high number of biotechnology offerings, as seen in figure 1.

Pre-Listing Return

The market return will be calculated for two months, measured by 42 trading days prior to the offering and will be log-transformed.

$$Pre - Listing\ Return = \log\left(1 + \frac{Closing\ Price_{m_0}}{Closing\ Price_{m_{-42}}}\right)$$

Issuer sentiment

In order to create variables that test for the effect of issuer sentiment, we make use of textual analysis. More specifically, using the Python programming language, we design algorithms that conduct sentiment analysis of S-1 filings. Consistent with empirical research, we only analyze the most important sections of a firm´s IPO prospectus[13]. We only focus on prospectus summary, risk factors, and M.D.A., and retrieve a polarity score for each section. This quantifies the issuers' attitude towards their offering. As we seek to test the effect of a more negative sentiment, a dummy is created for the lowest quartile for the polarity score of each section. This approach is similar to Ferris et al. (2012) who also set a limit for polarity score.

For the ease of readability and testing purposes, the program we built is split into two processes, one for text preprocessing and the second for the sentiment analysis itself. In order to analyze the sentiment of the sections of interest, a *txt-file* is prepared for each offering. Preprocessing contains functions and codes that are used for computer reading and extracting the desired sections from a firm´s S-1 filing. The first step is to read the S-1 filing for every company in our sample and create a *txt-file* for each section.

Every firm in our sample has a unique CIK number. We create an Excel file with a URL link that leads to a specific firm´s S-1 filing stored in the SEC´s EDGAR archive. The <read_text_from_html> function, implemented for reading *html* from a given URL is called and, as a result, UTF-8 encoded texts are returned. As all of these are still in *html-format*, we used *html-tags* for locating sections of interest and extracting those for analysis. For the purpose of parsing *html* and navigating through *html-text*, the Python library *BeautifulSoup* is used. The algorithm that does logic of locating the text of sections, starts with a function that locates the title "*Table of contents"* in the filing. For the vast majority of filings, Table of contents itself is

[13] See, among others: Hanley & Hoberg (2010), Ferris, Hao & Liao (2012)

located below the first “Table of contents” title, nested in *html* <table> tag and contains direct links to sections with *html* <a> tags.

After finding the links of the sections of interest, the algorithm proceeds with text extraction from prospectus summary, risk factors, and M.D.A sections. The beginning of the section is marked with a link (identified as *html* <a> tag with name property as *href* property from the link in the table of contents to that particular section) from previously found Table of contents and the end of it is the link to the next section, which is found in the same manner. After finding the beginning and ends of the sections, only the reading of pure text is done. The pure text is cleaned of *html-tags*, special characters, numbers, extra spaces and is saved to *txt-files* stored on the computer. The reading of the text is done with the function <text_between_tags> that iterates through *html-text*, tag by tag, and reads the pure text nested in those. The text is processed once again through the function <clean_text> before storing it in a *txt-format*. Finally, text from all three sections is stored with the firm´s CIK number as the name of the file with the purpose of easing identification.

After every S-1 filing is processed, and all the given sections are extracted, the sentiment analysis itself can be performed. Functions and codes are designed to read the previously found text of sections and analyze the sentiment of those using the Python library for text processing called *TextBlob*. First, all CIK numbers from our Excel file and the corresponding *txt-files* for all three sections are read. After all texts have been found, our program continues to wrap them in *TextBlob* in order to score their polarity. When the sentiment has been analyzed and a polarity score is assigned, these results are automatically stored in an Excel file, and the score of each firm is recognized by the firm´s CIK number.

We mentioned that we used *TextBlob* for our sentiment analysis. In addition to *TextBlob*, there are many other libraries intended for the use of NLP. NLP stands for Natural Language Processing and is a popular subfield within artificial intelligence. *TextBlob* provides application programming interfaces for most common NLP tasks and makes them easier to understand and perform. Further, *TextBlob* lies on top of NLTK – another platform for building Python programs that work with human language data[14]. As for the assigning of polarity, *TextBlob* uses Naive Bayes classifier to give a text float in the range [-1,1], where lower scores indicate more

[14] See TextBlob (n.d) and NLTK (n.d)

negative sentiment. The float is based on a body of pre-trained training data, and calculation of these scores is also based on the English lexicon which is stored internally in *TextBlob*.

3.2.3 Multiple regression models

Regression function for the abnormal return for the short-run:

$$Log(AR_{Short-run}) = \beta_0 + \beta_1 Bio + \beta_2 d_{2003-2008} + \beta_3 d_{2008-2010} + \beta_4 d_{2010-2014} + \beta_5 \ln(ADJ\ Offer\ Size_i) + \beta_6\ SQ\ \ln(ADJ\ Offer\ Size) + \beta_7 \ln(Pre-listing\ return) + \beta_8 \ln(Company_{Age}) + \beta_9 Underwriter + \beta_{10} VC + \beta_{11} \text{L. Q. Sent. (P. S.)} + \beta_{12} \text{L. Q. Sent. (R. F.)} + \beta_{13} \text{L. Q. Sent. (M. D. A.)} + \varepsilon$$

Regression function for the abnormal return for the long-run:

$$Log(AR_{Long-run}) = \beta_0 + \beta_1 Bio + \beta_2 d_{2003-2008} + \beta_3 d_{2008-2010} + \beta_4 d_{2010-2014} + \beta_5 \ln(ADJ\ Offer\ Size) + \beta_6\ SQ\ \ln(ADJ\ Offer\ Size) + \beta_7 \ln(Pre-listing\ return) + \beta_8 \ln(Company_{Age}) + \beta_9 Underwriter + \beta_{10} VC + \beta_{11} \text{L. Q. Sent. (P. S.)} + \beta_{12} \text{L. Q. Sent. (R. F.)} + \beta_{13} \text{L. Q. Sent. (M. D. A.)} + \varepsilon$$

3.2.4 OLS Violations

To determine the validity of a regression model, there are several potential violations of the ordinary least squares method that have to be investigated (Wooldridge, 2014). The potential violations that will be presented for our cross-sectional data are multicollinearity, heteroskedasticity, normality, and linearity.

Multicollinearity

Multicollinearity can be defined as high, but not perfect, correlation between two or more independent variables (Wooldridge, 2014). The problem of multicollinearity does not violate the assumptions of the OLS model, as long as there is no perfect correlation between the independent variables. If such a relationship exists, the statistical power of the regression will decrease. It is common that the independent variables of a regression will have a certain degree of correlation as they are created to explain effects on the same dependent variable. To

determine whether these effects point towards a severe problem of multicollinearity, a correlation matrix or a variance inflation factor (VIF) will be computed. A correlation above 0,8 between two independent variables or a VIF-indicator larger than 10 signifies a severe problem of multicollinearity.

Heteroskedasticity

The assumption of homoskedasticity for the OLS model fails whenever the variance of the unobserved factors changes across different segments of the population, meaning that the variance of the error term fails to be constant (Wooldridge, 2014). In the presence of heteroskedasticity, it does not cause bias or inconsistency in the OLS estimators of the coefficients. The goodness of fit measures are also unaffected by the presence of heteroskedasticity. However, heteroskedasticity will go against the Gauss-Markov theorem and the coefficients will no longer be the best linear unbiased estimator. To test whether the assumption of homoskedasticity holds, we will perform the White's test.

Non-normality

This assumption for normality states that the population error is independent of the explanatory variables and is normally distributed with zero mean and variance σ^2 (Wooldridge, 2014). A violation of the normality assumption will not contribute to bias or inefficiency in regression models, but will restrict tests of significance. The Jarque-Bera test will be used to determine whether there exists a problem with this assumption. However, for a large set of observations, the central limit theorem makes the distribution approximate towards normality.

Non-linearity

The linearity assumption depends on the dependent variable being a linear function of the independent variables (Wooldridge, 2014). This can be corrected for, as variables can be omitted or transformed to create a linear relationship. Ramsey's RESET test will be used to detect functional misspecification from the included variables.

4. Findings

4.1 Short-run performance

We find that the average market-adjusted underpricing for new listings is 16.6%. As described from table 4 the short-run performance varies, both in terms of cyclicality and level of underpricing across years. The highest underpricing occurred in 2013 with 27.2% and the lowest occurred in 2008 with 2%. This is in line with the presented literature in section 4.2, and similar to the findings of Bakke, Leite & Thorburn (2010) from their research on the time period of 1981-2008.

The average underpricing of companies in the biotechnology industry is found to be 17.7%, 1.3 percentage points higher relative to the rest of our sample. However, this difference is not statistically significant. Similarly, as seen by regression 5 in table 9, a positive non-significant coefficient for the biotechnology industry is detected when controlling for additional factors. The average underpricing of biotechnology companies is only higher in three calendar years relative to non-biotechnology companies, 2005, 2014 and 2015. We thereby reject hypothesis 1 of a higher level of underpricing for biotechnology companies. If the theory of higher underpricing for higher ex ante uncertainty holds, investors might not view biotechnology as risky as we have hypothesized. This might be enhanced by our choice of Nasdaq as our market, as we have explained that it is generally a market with many technology companies as well as smaller and more volatile companies. Ferris et al. (2012) argue that technology firms are more uncertain and difficult to value, which are characteristics that biotechnology also shares. Thus, the lack of significant difference for this coefficient can be explained by the fact that the companies we compare biotechnology to, simply are too similar to biotechnological companies.

The regressions show a positive significant relationship between the size of the offering and the level of underpricing. As the squared term is negatively significant, a concave relationship between the two exists. Thus, the positive effect is lessened as the offer size increases. A positive relationship between offer size and the level of underpricing contradicts existing literature given in section 2.7. However, it could be justified if large offer sizes generate more investor interest which in sense could facilitate an overoptimistic scenery. This scenery could, in turn, generate underpricing.

We find a significant positive relationship between the pre-listing market return and underpricing, indicating that IPOs in *bull* markets have a higher level of underpricing. Additionally, the average pre-listing market return of the IPOs in the dataset is 3%, indicating that IPOs generally go public during positive market periods. Furthermore, the underpricing increases with the pre-listing market return. This can also be an effect of issuers failing to fully adjust IPO prices to all publically available information, which is in line with the findings of Leite (2007). He argues that high market returns preceding the IPO, entice issuers to price their IPOs more conservatively, which in turn leads to a positive relation between market returns and underpricing.

VC-backed offerings and offerings underwritten by a prestigious underwriter have statistically significant positive short-run returns. Megginson & Weiss (1991) document the opposite of our findings regarding VC-backed IPOs. In our sample, VC-backed firms are approximately twice the age of non-VC-backed firms on average when going public. Specifically, VC-backed firms have a mean age of 9.6, while their counterparts are on average 20.9 years old. Consistent with Ritter (1984), firm age serves well as a proxy for uncertainty by the logic that younger firms do not have a proven track record and viability of their business model over time. Beatty & Ritter (1986) argue that underpricing increases with the ex ante uncertainty, which can explain the higher underpricing for VC-backed firms. This effect is further enhanced by Ruhnka & Young (1991) who show that VCs invest in ventures that involve a lot of uncertainty and risk.

While we find significantly positive effects of prestigious underwriters on underpricing, the majority of literature finds the opposite. On the other hand, our findings of a positive relation between underwriter quality and underpricing are in line with Beatty & Welch (1996) who investigated the dot-com bubble. They argue that high-quality underwriters and high-quality legal counsel serve as substitutes. They find that there was more underpricing in IPOs with high-quality underwriters, and justify their findings by the assumption that high-quality legal counsel do a better job at insuring against litigation risk without resorting to underpricing. Further, they posit that high-quality underwriters perhaps are more concerned with their reputation in order for future repeat business. Limiting the risk of litigation is one reputational concern that is mentioned by Beatty & Welch (1996). Our similar findings can be a result of the choice of exchange, as Nasdaq can be perceived as technology-heavy and result in a higher degree of underpricing for the prestigious underwriters.

Furthermore, the regressions find a significantly negative relationship between the companies that are in the lowest quartile in terms of polarity of the prospectus summary and the level of underpricing. The relationship between the sentiment of the lowest quartile of risk factors and M.D.A and underpricing is not statistically significant. We thereby find some evidence in support of our second hypothesis of less underpricing in a conservative filing, but cannot conclude for the sentiment of the prospectus as a whole from our results. As the M.D.A section of the prospectus is more future-oriented, it might explain why this variable is not significant in explaining short-run underpricing. The insignificance of the risk factor variable, however, is somewhat more surprising. As this section should indicate risk factors specific to the issuer, it should affect the ex ante uncertainty and the level of underpricing. Nevertheless, it could be explained by the aforementioned logic that issuers and underwriters either deliberately underprice their offers or apply a very reserved approach in their prospectus in order to insure against litigation risk[15]. As the risk factor variable is not significant, the former approach of deliberate underpricing might be dominating. Nonetheless, the negative coefficient of the prospectus summary is consistent with the argument that a cautious approach serves as insurance against litigation. Therefore, the firm does not need to deliberately underprice in order to achieve the same objective. In conclusion, our findings are rather ambiguous, as are the findings of existing literature.

[15] See, among others: Arnold et al. (2010) and Lowry & Shu (2002)

Year	2003	2004	2005	2006	2007	2008	2009	2010
Non-Biotechnology	0.160	0.127	0.100	0.141	0.194	0.020	0.182	0.134
Biotechnology	0.090	0.014	0.147	0.033	0.050	-	-0.133	0.033
Full Sample	0.154	0.118	0.103	0.138	0.183	0.020	0.161	0.121
N (Non-Bio)	24	59	54	55	61	10	14	34
N (Bio)	2	5	3	2	5	0	1	5
Year	**2011**	**2012**	**2013**	**2014**	**2015**	**2016**	**2017**	
Non- Biotechnology	0.193	0.167	0.274	0.151	0.165	0.174	0.185	
Biotechnology	0.148	0.101	0.264	0.291	0.259	0.050	0.047	
Full Sample	0.190	0.158	0.272	0.181	0.184	0.159	0.165	
N (Non-Bio)	35	39	55	84	58	45	51	
N (Bio)	2	6	19	23	15	6	9	

Table 4 – Average yearly short-run abnormal return. Described for biotechnology, non-biotechnology and the full sample. Number of offerings within biotechnology and non-biotechnology also given by year.

4.2 Long-run performance

We find that IPOs outperform the market by 1.6 percentage points on average after one year of trading. However, the median is negative and the average abnormal return is not statistically positive. Similar to the findings of short-run abnormal returns, the long-run performance differs over time as well. While the lowest level of long-run performance is found in 2011 and amounts to -25.3%, the highest level is seen in 2003 with 27% as shown in table 5. Although the literature generally depicts a long-run negative abnormal return of new offerings, a time period of one year is perhaps not adequate. Ritter (1991), for instance, finds that the initially positive performance usually starts to reverse into a negative long-run performance 12 months after the IPO.

Biotechnology offerings have a lower, non-significant, average long-run abnormal return with 0.25%, relative to the 1.75% found for non-biotechnology companies. Regression 10 from table 9 shows a non-significant negative relationship for the industry-specific variable for biotechnology, where additional factors are accounted for. Thus, we cannot reject our hypothesis that performance does not differ between biotechnology and non-biotechnology companies in the long-run. This is indicative of perhaps no fundamental changes in biotechnological firms within one year that could explain changes in performance relative to other industries. Although this is what we expect, as previously discussed, an exchange

consisting of companies with similar characteristics to biotechnology companies, might affect these results.

We find a statistically significant and positive effect of offer size on long-run performance. Also, a significant concave relationship represented by the squared term of the offer size is found. This implies offer size has a diminishing effect on long-run performance. This is consistent with previously mentioned literature of how larger firms, represented by larger offer sizes, are perceived as more reliable and less risky relative to smaller firms (Ritter 1991).

In addition, building on our argument in the section of short-run performance, where it was stated that larger issues might create more interest among investors, one could argue that this leads to more analyst coverage. By extension, such coverage could lead to more precisely priced IPOs and relatively better long-run performance. However, this contradicts our justification of the same effect on short-run performance. Therefore, our results are quite ambiguous.

Further, consistent with literature[16], we also find a positive significant relationship between the age of the company at the time of the offering and long-run performance. The same logic of how larger firms are perceived as more reliable and less risky applies to the age coefficient. Older firms have proven that their business is viable over a longer time period, and our findings point to this.

Moreover, we find a negative significant relationship between the pre-listing market return and the abnormal return after one year of trading. This can be a consequence of companies going public when equity is overvalued (Bayless & Chaplinsky, 1996). As described in the literature review, in *bull* markets there might be a *window of opportunity*. When equity is overvalued, the market price may be set higher than the stock´s fundamental value. This is then corrected for to a certain extent after one year of trading, resulting in poor long-run performance. Ritter (1991) documents this effect and argues that it is a result of investors periodically being overoptimistic about future growth.

IPOs that are underwritten by top-tier underwriters perform significantly better after one year of trading relative to companies that hired less prestigious underwriters. This is in line with the

[16] See Clark (2002) and Ritter (1991)

presented literature that suggests top-tier underwriters screen for the best candidates. Another plausible explanation is the one of Booth & Smith (1986), which argues that prestigious underwriters more efficiently certify that the issue price is consistent with inside information regarding the firm´s future. By doing so, the firm is priced closer to its true value, and by extension limiting fluctuations below true value.

After testing for the sentiment of the filings, we find effects pulling in opposite directions. On the one hand, there is a significant positive relationship for the lowest quartile of polarity score in the prospectus summary, indicating that companies in this quartile perform better in the long-run. The prospectus summary briefly outlines the business with key information of the firm. A possible explanation for the relatively better long-run performance of firms in the lowest quartile is that they have more reservations and apply a cautious approach. This deems the firm more credible and allows investors to factor in these reservations. Thus, limiting the downside. Our notion that more reservations and a cautiousness deems the prospectus more credible by investors, is addressed in Ferris et al. (2012).

We find a significant negative relationship between long-run performance and sentiment of the firms in the lowest quartile of the risk factor polarity score. This indicates that a more reserved approach for this section has a negative effect on long-run performance. This differs from the effect of the sentiment in the prospectus summary and might be explained based on the nature of the prospectus sections. While the prospectus summary, as explained in the previous paragraph, might signal the sentiment of the entire prospectus, the section for risk factors might be better to determine the degree of challenges an offering is facing. Meaning that a relatively more negative score for risk factors does not signal a cautious approach, but highlights the fact that the offering has a higher degree of uncertainty.

Moreover, the M.D.A coefficient, which is the most future-oriented of the tree, is statistically insignificant, and one could argue that this section would impact the long-run performance the most. Nevertheless, a time frame of one year might not be adequate in capturing the effect of the sentiment in this section.

We thereby reject the hypothesis that the prospectus sentiment does not affect long-run performance of an IPO, but are unable to draw clear conclusions as the effects pull in different directions.

Year	**2003**	**2004**	**2005**	**2006**	**2007**	**2008**	**2009**	**2010**
Non-Biotechnology	0.303	0.060	0.130	0.039	-0.140	-0.005	-0.182	0.123
Biotechnology	-0.132	0.165	-0.015	-0.593	-0.216	-	-0.295	-0.121
Full Sample	0.270	0.068	0.122	0.017	-0.145	-0.005	-0.190	0.0917
# Non-Bio	24	59	54	55	61	10	14	34
# Bio	2	5	3	2	5	-	1	5
Year	**2011**	**2012**	**2013**	**2014**	**2015**	**2016**	**2017**	
Non-Biotechnology	-0.268	0.161	-0.067	0.060	-0.212	0.013	0.241	
Biotechnology	0.017	0.381	-0.118	0.147	-0.317	0.124	0.385	
Full Sample	-0.253	0.191	-0.080	0.079	-0.234	0.026	0.263	
# Non-Bio	35	39	55	84	58	45	51	
# Bio	2	6	19	23	15	6	9	

Table 5 – Average yearly long-run abnormal return. Described for biotechnology, non-biotechnology and the full sample. Number of offerings within biotechnology and non-biotechnology also given by year.

4.3 Sample Descriptive Statistics

From table 6, the variables used in the thesis is described.

Variables	**Mean**	**Median**	**Min.**	**Max.**	**St. Dev.**	**Skew.**	**Kurt.**
AR Short-run	0.166	0.105	-0.411	2.049	0.261	2.162	11.052
AR Long-run	0.016	-0.083	-1.171	5.350	0.678	1.910	10.562
Company Age	16.353	9.000	0.000	165.000	22.186	3.422	16.077
ADJ Offer Size	166.830	96.997	4.240	17089.346	637.948	24.126	636.129
VC	0.401	0.000	0.000	1.000	0.490	0.405	1.164
Underwriter	0.415	0.000	0.000	1.000	0.493	0.346	1.119
Biotechnology	0.132	0.000	0.000	1.000	0.339	2.176	5.734
Pre-Listing Return	0.030	0.032	-0.364	0.205	0.054	-0.716	6.970
Sent. (P.S.)	0.054	0.052	-0.069	0.208	0.029	0.694	5.832
Sent. (R.F.)	0.049	0.049	-0.190	0.163	0.016	-3.951	71.578
Sent. (M.D.A.)	0.052	0.052	-0.036	0.114	0.018	-0.203	4.240
2003-2008	0.346	0.000	0.000	1.000	0.476	0.649	1.421
2008-2010	0.032	0.000	0.000	1.000	0.176	5.317	29.273
2010-2014	0.250	0.000	0.000	1.000	0.433	1.157	2.338
N	781	781	781	781	781	781	781

Table 6 – Descriptive statistics for the full sample. Given are the mean, median, minimum and maximum observation, standard deviation, skewness and kurtosis for each variable.

Variables	Non-Biotechnology	Biotechnology
AR short-run	0.164	0.177
AR long-run	0.0175	0.00254
Company Age	17.62	8.010
ADJ Offer Size	178.6	89.39
VC	0.367	0.621
Underwriter	0.423	0.359
Pre-Listing Return	0.0298	0.0288
Sentiment (P.S.)	0.0560	0.0446
Sentiment (R.F.)	0.0482	0.0527
Sentiment (M.D.A)	0.0514	0.0551
N	678	103

Table 7 – Variable averages for biotechnology and non-biotechnology

From table 7, the differences between the characteristics of a biotechnology company relative to a non-biotechnology company are described. Companies within biotechnology tend to be younger, which fits the reasoning that they go public in order to fund initial research. Furthermore, biotechnology companies tend to be smaller and more frequently backed by venture capital relative to non-biotechnology.

In terms of the sentiment of the prospectus, we find a relatively more negative score for biotechnology companies within the prospectus summary. The section of risk factors and M.D.A have a more positive score relative to non-biotechnology companies. However, the differences of all the three analyzed sections of the filing are not found to be statistically significant. We are thereby not able to prove that companies within the biotechnology industry have a more conservative filing compared to other offerings. Related to previous discussions, this might be a result of similarities of biotechnology relative to the benchmark companies at Nasdaq.

Figure 2 below graphs the characteristics of the offer size adjusted for inflation. The small offerings are defined to be the number of firms with a lower offer size than the mean of the sample, while the large offerings have a larger offer size relative to the average. The number of small offerings outnumbers the large offerings and the average offer size is relatively stable over the years. The offer size had its highest peak in 2012 when Facebook went public.

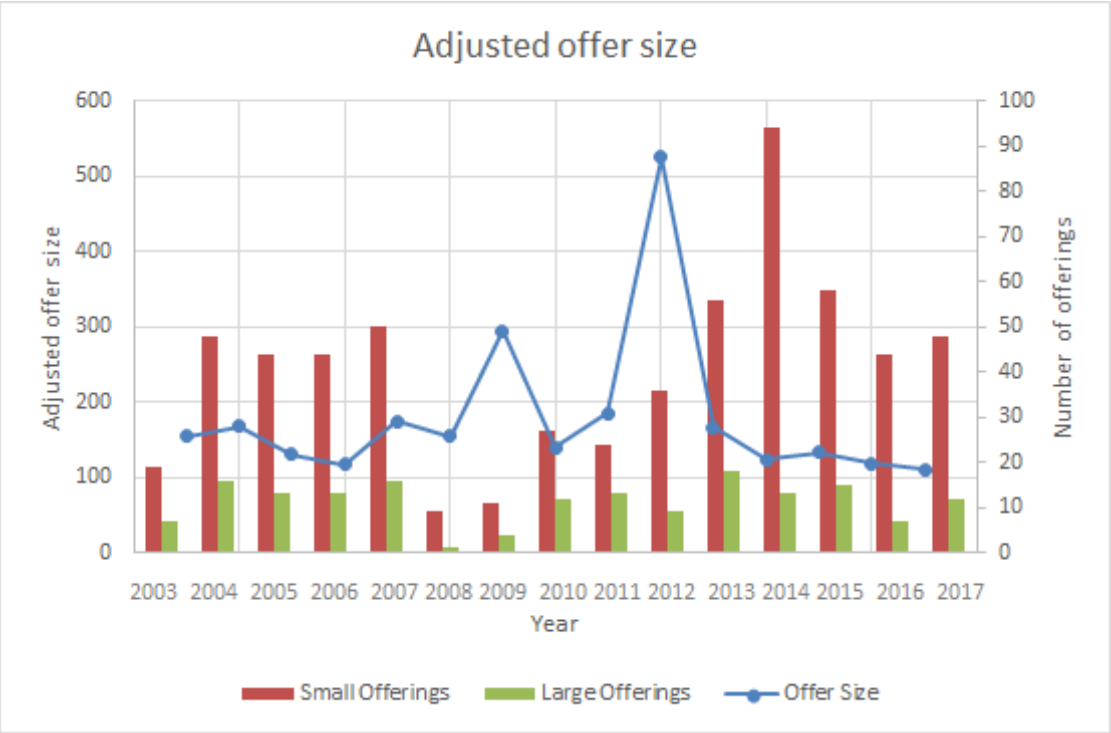

Figure 2 – The average adjusted offer size and number of small and large offerings by year.

4.4 Testing OLS violations

4.4.1 Multicollinearity

Multicollinearity is detected through the correlation matrix found in table 10 of appendix B, and through calculation of the variance inflation indicator (VIF) found in table 11 of appendix B. We do not find a correlation higher than 0.8 or a VIF-value higher than 10, indicating that we do not have a severe problem of multicollinearity. The two highest values of correlation are found for underwriter and offer size, and the time periods 2003-2008 and 2010-2014, with a respective correlation of 0.395 and -0.419.

4.4.2 Heteroskedasticity

We perform White's test to determine whether there exists a problem of heteroskedasticity or not. The test output for the short-run generates a χ^2 – value of 102.34 and a P-value of 0.0337. For the test of IPO performance in the long-run, the White's test generates a χ^2 – value of 63.13 and a P-value of 0.8891. The null hypothesis of homoskedasticity is thereby rejected for the short-run regression, but not rejected in the long-run. According to the Gauss-Markov theorem,

the short-run regressions will no longer be the best unbiased linear estimator. Therefore, the more conservative approach of robust standard errors is used. Heteroskedasticity is not a problem for long-run performance as the null hypothesis was not rejected.

4.4.3 Non-Normality

The test output for the Jarque-Bera skewness-kurtosis test generates a P-value of less than 5% for both the short- and long-run. This rejects the null hypothesis of normality. The use of log-transformed dependent- and certain independent variables have been made to improve the normality of the variables, but not sufficiently to achieve normality. Box-plots and Kernel distribution of the dependent variable for the short- and long-run can be found in figure 3 through figure 6 of appendix A. The visuals seem to show that there might be outliers that possibly are causing the detected non-normality. Outliers are not excluded, but were investigated to make sure that there are no data errors involved.

However, as explained previously, the criteria of normality can be loosened if the number of observations is large. 781 IPOs can be regarded as a large number of observations, which makes the central limit theorem hold.

4.4.4 Non-Linearity

The Ramsey's RESET test shows that there might be omitted variables as the test output generates a p-value lower than 5% in the short-run. The inclusion of squared terms is thereby included in our regressions, with the coefficients included in the tables 12 and 13 of appendix B. We find that the squared term of offer size is statistically significant for our short- and long-run regressions. The negative coefficient shows a quadratic relationship of offer size and is added to our regressions.

4.5 Regression results

4.5.1 Short-run

Variables	Reg. 1	Reg. 2	Reg. 3	Reg. 4	Reg. 5
Biotechnology	-0.000853	0.0113	0.000901	0.00498	0.000868
	(0.0242)	(0.0236)	(0.0235)	(0.0235)	(0.0233)
Ln(Company Age)		0.00169	0.0106	0.00948	0.00999
		(0.00732)	(0.00718)	(0.00722)	(0.00728)
Ln(ADJ Offer Size)		0.179***	0.145***	0.144***	0.155***
		(0.0349)	(0.0359)	(0.0367)	(0.0369)
SQ Ln(ADJ Offer Size)		-0.0126***	-0.0100***	-0.0102***	-0.0111***
		(0.00337)	(0.00354)	(0.00363)	(0.00361)
Ln(Pre-Listing Return)		0.431***	0.429***	0.433***	0.410***
		(0.0981)	(0.0996)	(0.100)	(0.106)
VC			0.0578***	0.0608***	0.0550***
			(0.0144)	(0.0146)	(0.0150)
Underwriter			0.0338**	0.0329**	0.0338**
			(0.0154)	(0.0153)	(0.0154)
L.Q. Sent. (P.S)				-0.0331**	-0.0318**
				(0.0146)	(0.0146)
L.Q. Sent. (R.F.)				0.0229	0.0211
				(0.0146)	(0.0145)
L.Q. Sent. (M.D.A.)				0.0119	0.0115
				(0.0155)	(0.0155)
2003-2008					-0.0220
					(0.0158)
2008-2010					-0.0583
					(0.0361)
2010-2014					-0.00730
					(0.0189)
_cons	0.133***	-0.434***	-0.390***	-0.382***	-0.397***
	(0.00729)	(0.0890)	(0.0904)	(0.0929)	(0.0923)
N	781	781	781	781	781
R^2	0.000	0.086	0.114	0.122	0.126

Standard errors in parentheses
* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Table 8 – The table reports the coefficients and corresponding standard error (in parenthesis) from the regressions. The regressions are run with the log-transformed abnormal short-run return as the dependent variable. Factors that are assumed to affect the abnormal return are set as independent variables. Regressions are run with robust standard errors.

4.5.2 Long-run

Variables	Reg. 6	Reg. 7	Reg. 8	Reg. 9	Reg. 10
Biotechnology	-0.0644	-0.0421	-0.0408	-0.0576	-0.0652
	(0.0672)	(0.0679)	(0.0686)	(0.0688)	(0.0695)
Ln(Company Age)		0.0696**	0.0783***	0.0793***	0.0806***
		(0.0270)	(0.0277)	(0.0277)	(0.0279)
Ln(ADJ Offer Size)		0.466***	0.420***	0.429***	0.445***
		(0.144)	(0.146)	(0.147)	(0.149)
SQ Ln(ADJ Offer Size)		-0.0449***	-0.0425***	-0.0428***	-0.0445***
		(0.0148)	(0.0148)	(0.0149)	(0.0151)
Ln (Pre-Listing Return)		-0.929**	-0.935**	-0.926**	-1.026**
		(0.418)	(0.417)	(0.417)	(0.424)
VC			0.0130	0.0111	-0.00192
			(0.0481)	(0.0484)	(0.0506)
Underwriter			0.0957*	0.0998**	0.101**
			(0.0507)	(0.0506)	(0.0507)
L.Q. Sent. (P.S.)				0.0988*	0.103*
				(0.0525)	(0.0526)
L.Q. Sent. (R.F.)				-0.0913*	-0.0945*
				(0.0528)	(0.0530)
L.Q. Sent. (M.D.A.)				0.0461	0.0475
				(0.0527)	(0.0530)
2003-2008					-0.0230
					(0.0560)
2008-2010					-0.131
					(0.133)
2010-2014					0.0316
					(0.0595)
_cons	-0.169***	-1.479***	-1.383***	-1.432***	-1.462***
	(0.0244)	(0.358)	(0.361)	(0.365)	(0.366)
N	781	781	781	781	781
R^2	0.001	0.029	0.033	0.042	0.045

Standard errors in parentheses
* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Table 9 – The table reports the coefficients and corresponding standard error, in parenthesis, from the regressions. The regressions are run with the log-transformed abnormal long-run return as the dependent variable. Factors that are assumed to affect the abnormal return is set as independent variables. Regressions do not suffer from heteroskedasticity.

4.6 Research Reliability and Limitations

The data used in this thesis is collected from different sources. Although our best efforts have been made to control for errors in the data, there exists a possibility of differences among sources. Part of the dataset used has been collected manually, which leaves the chance of human error to encounter.

The use of Nasdaq as a benchmark might be misleading as the exchange is regarded as more volatile with companies that have less historical track record compared to larger exchanges like the New York Stock Exchange. We also assumed that the exchange is not overly concentrated around technology stocks. Too high of a contraction of these kinds of stocks might leave the benchmark to similar to the nature of biotechnology companies.

In hindsight, based on our lack of significant differences between biotechnology- and non-biotechnology firms, we are left with several insights. For instance, it is quite plausible that some non-biotechnology firms in our sample have too similar characteristics to biotechnology firms. A more plausible approach would be to further distinguish between biotechnology and industries within our comparative sample that resemble the characteristics of biotechnology. In high-technology industries such as IT and computer software, product development and sales are also uncertain (Ferris et al. 2012). Therefore, had we been able to easily distinguish between such characteristics and compared biotechnology to a more refined sample, we might have received more significant results.

As aforementioned, the greatest shortcoming of our sentiment analysis is the dictionary on which the sentiment scores are based. However, it is the most comprehensible given our familiarity with Python. The Naive Bayes classifier *TextBlob* uses, and NLTK, are pre-trained with training data that has originated from movie reviews, making it less suitable for analyzing financial texts. Therefore, there exists a likelihood that some common financial words could be misclassified. A better option would be to use the dictionary Loughran & McDonald (2010) created. Their dictionary could perhaps capture the tone of IPO prospectuses in a better manner as it is compiled from financial sources such as, for instance, 10-K filings. Further, our program for processing S-1 filings is not capable of extracting sections of interest if the firm´s S-1 is in *txt-format* in the Edgar archive. Hence, these firms must be excluded, which in turn reduces our sample by 13 offerings. As 188 companies from our initial sample had their S-1 stored without

a table of contents with links to sections, we had to omit them from our final sample. This is common practice in empirical works as the field of machine reading is relatively new (Hanley & Hoberg, 2010). Our analysis leads to fewer omissions as our programming circumvented the problem of Hanley & Hoberg (2010), whose textual analysis could not extract all prospectus summary sections. While they have to omit companies where the section was labeled *Summary* instead of *Prospectus Summary*, our textual analysis is able to extract both forms. We ended up with 781 firms in our sample, which we deem acceptable.

5. Conclusion

This thesis has been written to investigate the IPO performance and sentiment analysis of biotechnology offerings at Nasdaq in the time period of 2003 - November 17th, 2017. We have found the most interesting part of our analysis to be the lack of verification of differences between biotechnology and non-biotechnology companies. Even though we are unable to draw clear conclusions, the performed analysis provides insights into the IPO market for biotechnology companies.

In line with previous research, we do find the presence of underpricing in our sample. The cyclicality of IPOs over the years, both in terms of the number of filings and varying degree of underpricing is found. We find the average market-adjusted underpricing to be 16.6%, where the underpricing for biotechnology companies is 1.3 percentage points higher relative to non-biotechnology companies. This difference is not statistically significant, as is the case from our regressions when we control for more variables.

Our textual analysis does not provide clear conclusions for all our investigated sections. We do find that companies in the lowest quartile in terms of polarity of the section prospectus summary have less underpricing. This points to an effect that a more reserved and cautious prospectus serves as a substitute for underpricing in regards to insurance against litigation.

Our control variables indicate that the market return at Nasdaq in the two months prior to an offering affects the underpricing positively. Both VC-backed offerings and offerings underwritten by prestigious underwriters have a higher degree of underpricing. The effect of the offer size is found to have a positive concave relationship on the underpricing of an offering. These variables, with the exception of a prestigious underwriter and offer size, are in line with the majority of the previous literature.

We do not find worse performance in the long-run for the offerings in our sample relative to the market benchmark. This could be due to our chosen timeframe to limit the probability of a biotechnology offering completing their current test phase. The average market-adjusted long-run performance is 1.6%. The performance is however not statistically significant, and we find no evidence that biotechnology companies perform differently relative to non-biotechnology

companies in the long-run. The performance of a biotechnology relative to a non-biotechnology company does not change when more variables are included in our performed regressions.

The results of the textual analysis for long-run performance are conflicting. We find evidence in favor of certain sections affecting the long-run performance of an offering. Offerings in the lowest quartile of the prospectus summary have stronger performance, while the companies in the lower quartile of the risk factors perform worse. The former effect is argued to be a consequence of investors deeming such companies more credible as they can factor in listed reservations in the prospectus summary. The effect of a relatively more negative sentiment in the risk factor section, however, portrays that the company has more uncertainty. Moreover, we do not find the M.D.A section, which is arguably the most likely section to impact long-rung performance, to be significant. This is possibly a consequence of a one-year time frame being too short to capture its effect. The hypothesis that the issuer sentiment has no effect on long-run performance is thereby rejected.

Our control variables for the long-run performance seem to match the findings of other researchers. The age of the company at the time of offering and the offer size have a positive effect on the long-run performance. Similarly, offerings making use of a prestigious underwriter perform better than those who do not use prestigious underwriters. Our control variable for the market return prior to listing is negative, meaning that we might have the case of performance reversal.

In general, biotechnology companies are not found to have a statistically significant difference in polarity score in any of the three sections that are investigated, although the section of prospectus summary is, on average, more conservative relative to non-biotechnology companies.

6. References

Aggarwal, R., & Rivoli, P. (1991). Evaluating the costs of raising capital through an initial public offering. *Journal of Business Venturing, 6*(5), 351-361.

Aggarwal, R., Leal, R., & Hernandez, L. (1993). The Aftermarket Performance of Initial Public Offerings in Latin America. *Financial Management, 22*(1), 42-53.

Aggarwal, R., Prabhala R., N., & Puri, M. (2002). Institutional Allocation In Initial Public Offerings: Empirical Evidence. *Journal of Finance, 57*, 1421-1442.

Allen, F., & Faulhaber, G. R. (1989). Signaling by underpricing in the IPO market. *Journal of Financial Economics, 23*(2), 303-323.

Amihud, Y., Hauser, S., & Kirsh, A. (2003). Allocations, adverse selection, and cascades in IPOs: Evidence from the Tel Aviv Stock Exchange. *Journal of Financial Economics, 68*(1), 137-158.

Ang, J. S., & Brau, J. C. (2003). Concealing and confounding adverse signals: insider wealth-maximizing behavior in the IPO process. *67*(1), 149-172.

Arnold, T., Fishe, R. P., & North, D. (2010). The Effects of Ambiguous Information on Initial and Subsequent IPO Returns. *Financial Management, 39*(4), 1497-1519.

Bakke, E., Leite, T. E., & Thorburn, K. S. (2010). *Public Information and IPO Underpricing.* Retrieved from https://brage.bibsys.no/xmlui//bitstream/handle/11250/164157/dpfor2010-6.pdf?sequence=1&isAllowed=y

Bakke, E., Leite, T., & Thorburn, K. S. (2017). Partial adjustment to public information in the pricing of IPOs. *Journal of Financial Intermediation, 32*, 60-75.

Bayless, M., & Chaplinsky, S. (1996). Is There a Window of Opportunity for Seasoned Equity Issuance? *Journal of Finance, 51*(1), 253-278.

Beatty, P. R., & Welch, I. (1996). Issuer expenses and legal liabilty in initial public offerings. *Journal of Law and Economics, 39*(2), 545-602.

Beatty, R. P., & Ritter, J. R. (1986). Investment banking, reputation, and the underpricing of initial public offerings. *Journal of Financial Economics, 15*(1-2), 213-232.

Benveniste, L. M., & Spindt, P. A. (1989). How investment bankers determine the offer price and allocation of new issues. *Journal of Financial Economics, 24*(2), 343-361.

Berk, J., & Demarzo, P. (2014). *Corporate Finance.* Essex: Pearson Education.

Bio. (n.d.). Retrieved 11 2018, from Bio: https://www.bio.org/what-biotechnology

Black, B., & Gilson, R. J. (1998). Venture capital and the structure of capital markets: banks versus stock markets. *Journal of Financial Economics, 47*(3), 243-277.

Bloomberg Terminal. (n.d.).

Bonala, S. (2016). *Biostandups.* Retrieved from http://www.biostandups.com/bio-tech/countries-leading-biotechnology-industry-global-rankings/

Booth, B. (2017). Retrieved from Forbes: https://www.forbes.com/sites/brucebooth/2017/11/17/painful-truth-successful-failure-of-a-biotech-startup/#3fe801a2d025

Booth, J. R., & Smith, R. (1986). Capital raising, underwriting and the certification hypothesis. *Journal of Financial Economics, 15*(1-2), 261-281.

Brau, J. C., & Fawcett, S. E. (2006). Initial Public Offerings: An Analysis. *The Journal of Finance, 61*(1), 399-436.

Brau, J. C., Bill, F., & Kohers, N. (2003). The Choice of IPO versus Takeover: Empirical Evidence. *The Journal of Business, 76*(4), 583-612.

Brav, A., & Gompers, P. A. (1997). Myth or Reality? The Long-Run Underperformance of Initial Public Offerings: Evidence from Venture and Nonventure Capital-Backed Companies. *The Journal of Finance, 52*(5), 1791-1821.

Bravo, A. (1998). *Inference in Long Horizon Event Studies: A Bayesian Approach with Application to Initial Public Offerings*. Retrieved 2018, from https://papers.ssrn.com/sol3/papers.cfm?abstract_id=90253

Brennan, M. J., & Franks, J. (1997). Underpricing, ownership and control in initial public offerings of equity securities in the UK. *Journal of Financial Economics, 45*(3), 391-413.

Brennan, M. J., & Subrahmanyama, A. (1996). Market microstructure and asset pricing: On the compensation for illiquidity in stock returns. *Journal of Financial Economics, 41*(3), 441-464.

Brown, S. J., Goetzmann, W., Ibbotson, R. G., & Ross, S. A. (1992). Survivorship Bias in Performance Studies. *The Review of Financial Studies, 5*(4), 553-580.

Bureau of Labor Statistics. (2018, November). *Consumer Price Index (CPI) Databases*. Retrieved from https://www.bls.gov/cpi/data.htm

Celikyurt, U., Svilir, M., & Shivdasani, A. (2010). How an IPO Helps in M&A. *Journal of Applied Corporate Finance*(2), 94-99.

Chemmanur, T. J., & Fulghieri, P. (1999). A Thoery of the Going-Public Decision. *The Review of Financial Studies, 12*(2), 249-279.

Clark, D. T. (2002). A Study of the Relationship Between Firm Age-at-IPO and Aftermarket Stock Performance . *Financial Markets Institutions and Instruments, 11*(4), 385-400.

De Bondt, W. F., & Thaler, R. (1985). Does the Stock Market Overreact. *The journal of Finance, 40*(3).

De Bondt, W. F., & Thaler, R. H. (1987). Further Evidence on Investor Overreaction and Stock Market Seasonality. *The Journal of Finance, 42*(3).

Desjardins, J. (2017). *Business Insider.* Retrieved from https://www.businessinsider.com/heres-the-difference-between-the-nasdaq-and-nyse-2017-7?r=US&IR=T&IR=T

DiMasi, J. A., Grabowski, H. G., & Hansen, R. W. (2003). The price of innovation: new estimates of drug development costs. *Journal of Health Economics, 22*, 151-185.

Dong, M., Michel, J.-S., & Pandes, J. A. (2011). Underwriter Quality and Long-Run IPO Performance. *Financial Management, 4*(1), 219-251.

Drake, P. D., & Vetsuypens, M. R. (1993). IPO Underpricing and Insurance Against Legal Liability. *Financial Management, 22*(1), 64-73.

Eckbo, E. B., & Norli, Ø. (2002). Pervasive Liquidity risk. *Working paper, Tuck School of Business at Dartmouth*.

Eckbo, E. B., & Norli, Ø. (2005). Liquidity risk, leverage and long-run IPO returns. *Journal of Corporate Finance, 11*(1-2), 1-35.

Efrata, T. (2008). R&D Intensity and IPO Underpricing: Case Study on Pharmaceutical and Biotech Industries in the US. *Accounting and Investment Journal, 9*(1), 1-21.

EY. (2016, August). *Best practices when going through the IPO registration process*. Retrieved November 2018, from https://www.ey.com/Publication/vwLUAssets/EY_-_Best_practices_when_going_through_the_IPO_registration_process/$FILE/ey-ipo-best-practices-ipo-registration-process.pdf

FDA. (2018, January). Retrieved October 2018, from https://www.fda.gov/ForPatients/Approvals/Drugs/default.htm

Ferris, S. P., Hao, G. Q., & Liao, M.-Y. (. (2012, April 10). The Effect of Issuer Conservatism on IPO Pricing and Performance. *Review of Finance, 17*(3), 993-1027.

Giudici, G., & Roosenboom, P. (2004). The long-run performance of initial public offerings on Europe´s new stock markets. *Advances in Financial Economics, 10*, 329-354.

Grinblatt, M., & Hwang, C. Y. (1989). Signalling and the Pricing of New Issues. *Jorunal of Finance, 44*(2), 393-420.

Hanley, K. W., & Hoberg, G. (2010). The Information Content of IPO Prospectuses. *The Review of Financial Studies, 23*(7), 2821–2864.

Ibbotson, R. G. (1975). Price Performance of Common Stock New Issues. *Journal of Financial Economics, 2*(3), 235-272.

Jovanovic, B., & Rousseau, P. L. (2001). Why Wait? A Century of Life Before IPO. *American Economic Review, 91*(2), 336-341.

Leite, T. (2007). Adverse selection, public information, and underpricing in IPOs. *Journal of Corporate Finance, 13*(5), 813-828.

Ljungqvist, A. (2004). *Handbooks in Finance: Empirical Corporate Finance.* (Eckbo, & B. Espen, Eds.) Elsevier BV.

Ljungqvist, A. (2007). *Handbook of Empirical Corporate Finance* (Vol. 1). (B. E. Eckbo, Ed.) Elsevier.

Ljungqvist, A., & Wilhelm Jr., W. J. (2003). IPO Pricing in the Dot-Com Bubble. *The Journal of Finance, 58*(2), 723-752.

Ljungqvist, A., & Wilhelm, W. (2002). IPO allocations: discriminatory or discretionary? *Journal of Financial Economics, 65*(2), 167-201.

Logue, D. E. (1973). On the Pricing of Unseasoned Equity Issues. *Journal of Financial and Quantitative Analysis, 8*(1), 91-103.

Loughran, T., & McDonald, B. (2010). *When is a Liability not a Liability? Textual Analysis, Dictionaries, and 10-Ks*. Retrieved from Working paper: https://papers.ssrn.com/sol3/papers.cfm?abstract_id=1331573

Loughran, T., & Ritter, J. (2004). Why Has IPO Underpricing Changed Over Time. *Financial Management, 33*(3), 5-37.

Loughran, T., & Ritter, J. R. (2002). Why Don´t Issuers Get Upset About Leaving Money on the Table in IPOs? *The Review of Financial Studies, 15*(2), 413-444.

Loughran, T., Ritter, J. R., & Rydqvist, K. (1994). Initial Public Offerings: International Insights. *Pacific-Basin Finance Journal, 2*, 165-199.

Lowry, M., & Shu, S. (2002). Litigation risk and IPO underpricing. *Journal of Financial Economics, 65*(3), 309-335.

Lowry, M., Officer, M. S., & Schwert, W. G. (2010). The Variablity of IPO Initial Returns. *The Journal of Finance, 65*(2).

Maksimovic, V., & Pichler, P. (2001). Technological Innovation and Initial Public Offerings. *The Review of Financial Studies, 14*(2), 459-494.

Maksimovic, V., & Unal, H. (1993). Issue Size Choice and "Underpricing" in Thrift Mutual-to-Stock Conversions. *The Journal of Finance, 48*(5).

McGuiness, P. (1992). An Examination of the Underpricing of Initial Public Offerings in Hong Kong: 1980-1990. *Journal of Business Finance & Accounting, 19*(2).

Megginson, W. L., & Weiss, K. A. (1991). Venture Capitalist Certification in Initial Public Offerings. *Journal of Finance, 46*(3).

Michaely, R., & Shaw, W. H. (1994). The Pricing of Initial Public Offerings: Tests of Adverse-Selection and Signaling Theories. *Review of Financial Studies, 7*(2), 279-319.

Milgram, S., Bickman, L., & Berkowitz, L. (1969). Note on the drawing power of crowds of different size. *Journal of Personality and Social Psychology, 13*(2), 79-82.

Miller, E. M. (1977). Risk, Uncertainty, and Divergence of Opinion. *The Journal of Finance, 42*(4).

Modigliani, F., & Miller, M. H. (1963). Corporate Income Taxes and the Cost of Capital: A Correction. *The American Economic Review, 53*(3), 433-443.

Myers, S. C., & Majluf, N. S. (1961). Corporate financing and investment decisions when firms have information that investors do not have. *Journal of Financial Economics, 13*(2), 187-221. Retrieved 11 15, 2018, from https://www.sciencedirect.com/science/article/pii/0304405X84900230

Nasdaq. (2018). Retrieved from Nasdaq Companies: https://www.nasdaq.com/screening/companies-by-industry.aspx?exchange=NASDAQ

Nasdaq OMX. (2018). Retrieved from https://indexes.nasdaqomx.com/Index/Overview/NBI

Neneh, B. N., & Smit, V. A. (2014). Do IPOs underperform in the long run? Evidence from the. *African Review of Economics of Finance, 6*(2).

NLTK. (n.d.). *NLTK*. Retrieved November 2018, from http://www.nltk.org/

Pastor, L., & Stambaugh, R. (2003). Liquidity Risk and Expected Stock Returns. *Journal of Political Economy, 111*(3), 642-685.

PhRMA. (2015). Retrieved 10 2018, from PhRMA: http://phrma-docs.phrma.org/sites/default/files/pdf/rd_brochure_022307.pdf

Picardo, E. (2018). *Investopedia.* Retrieved November 2018, from https://www.investopedia.com/terms/b/biotech-compound.asp

PWC. (2017, November). *Roadmap for an IPO A guide to going public*. Retrieved November 2018, from https://www.pwc.com/hu/hu/szolgaltatasok/konyvvizsgalat/szamviteli-tanacsadas/kiadvanyok/roadmap_for_an_ipo.pdf

Reilly, F. K., & Hatfield, K. (1969). Investor Experience With New Stock Issues. *Financial Analysts Journal, 25*(5), 73-80.

Reuter, J. (2004). *Are IPO Allocations for Sale? Evidence from Mutual Funds.* Working paper, University of Oregon.

Ritter, J. (2016). Retrieved from https://site.warrington.ufl.edu/ritter/files/2016/06/Underwriter-Rank-1980-2015.xls

Ritter, J. (n.d.). *A list of Rollup IPOs from 1980-2017*. Retrieved from Warrington College of Business: https://site.warrington.ufl.edu/ritter/files/2018/04/age7517.xls

Ritter, J. R. (1984). The "Hot Issue" Market of 1980. *The Journal of Business, 57*(2), 215-240.

Ritter, J. R. (1991). The Long-Run Performance of Initial Public Offerings. *The Journal of Finance, 46*(1), 3-27.

Rock, K. (1986). Why new issues are underpriced. *Journal of Financial Economics, 15*(1-2), 187-212.

Ruhnka, J. C., & Young, J. E. (1991). Some hypotheses about risk in venture capital investing. *Journal of Business Venturing, 6*(2), 115-133.

Rydqvist, K. (1997). IPO underpricing as tax-efficient compensation. *Journal of Banking & Finance, 21*(3), 295-313.

Shi, C., Pukthuanthong, K., & Walker, T. (2012). Does Disclosure Regulation Work? Evidence from International IPO Markets. *Contemporary Accounting Reserach, 30*(1).

Shiller, R. J. (1990). Speculative Prices and Popular Models. *The Journal of Economic Perspectives, 4*(2), 55-65.

Spiess, D. K., & Pettway, R. H. (1997). The IPO and first seasoned equity sale: Issue proceeds, owner/managers´ wealth, and the underpricing signal. *Journal of Banking & Finance, 21*(7), 967-988.

Steinbach, M. (2018). Retrieved from EY: https://www.ey.com/en_gl/growth/how-to-give-an-ipo-the-best-chance-of-long-term-success

Stoughton, N. M., & Zechner, J. (1998). IPO-mechanisms, monitoring and ownership structure. *Journal of Financial Economics, 49*(1), 45-77.

Taranto, M. A. (2003). *Employee Stock Options and the Underpricing of Initial Public Offerings.* Working paper. University of Pennsylvania.

TextBlob. (n.d.). *TextBlob: Simplified Text Processing*. Retrieved November 2018, from https://textblob.readthedocs.io/en/dev/

Tiniç, S. M. (1998). The Anatomy of Initial Public Offerings of Common Stock. *The Journal of Finance, 43*(4), 789-822.

Welch, I. (1989). Seasoned offerings, imitation costs, and the underpricing of Initial Public Offerings. *Journal of Finance*(2), 421-449.

Welch, I. (1992). Sequential Sales, Learning, and Cascades. *The Journal of Finance, 47*(2), 695-732.

Wooldridge, M. J. (2014). *Introduction to Econometrics.* Hampshire: Cengage Learning.

Zingales, L. (1995). Insider Ownership and the Decision to Go Public. *Review of Economic Studies, 62*(3), 425-448.

7. Appendices

7.1 Appendix A: Distribution of dependent variables

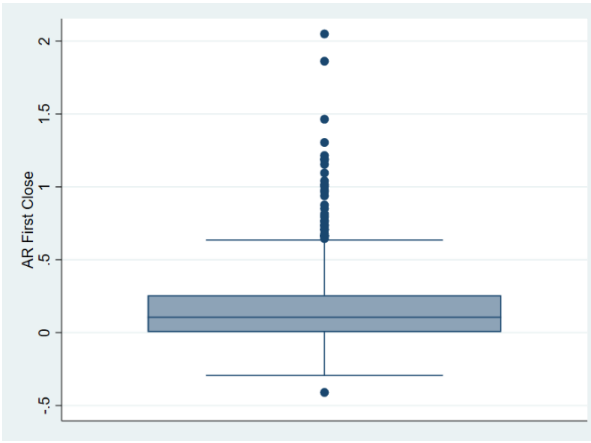

Figure 3 – Box-plot of the short-run abnormal return.

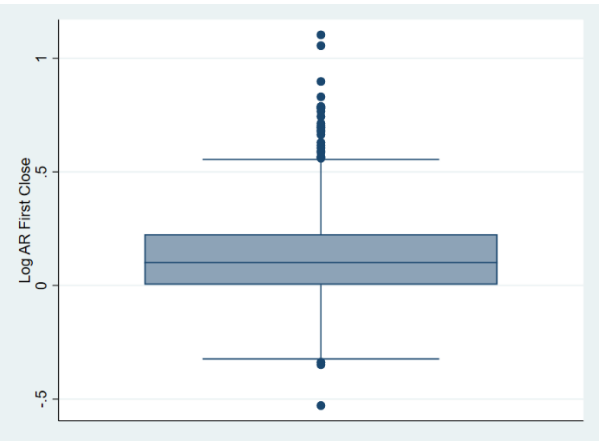

Figure 4 – Box plot of the short-run log-transformed abnormal return.

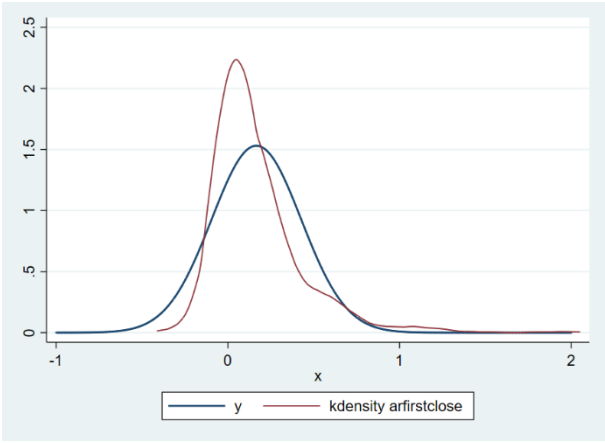

Figure 5 – Kernel density and normal distribution for the short-run abnormal return. Bandwidth for the Kernel distribution: 0.0729.

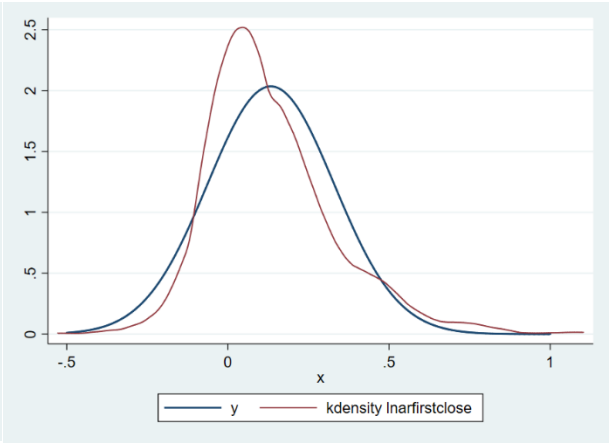

Figure 6 – Kernel density and normal distribution for the short-run log-transformed abnormal return. Bandwidth for the Kernel distribution: 0.0548.

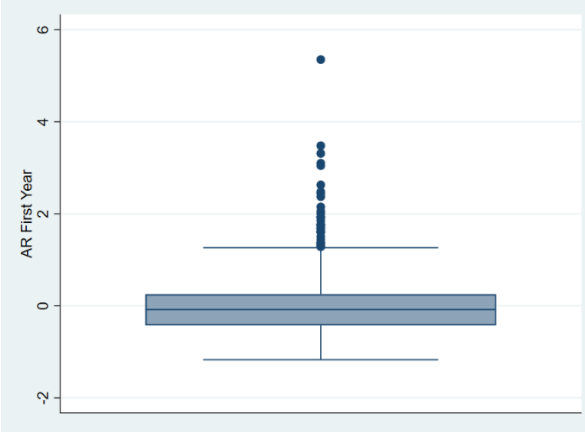

Figure 7 – Box-plot of the long-run abnormal return.

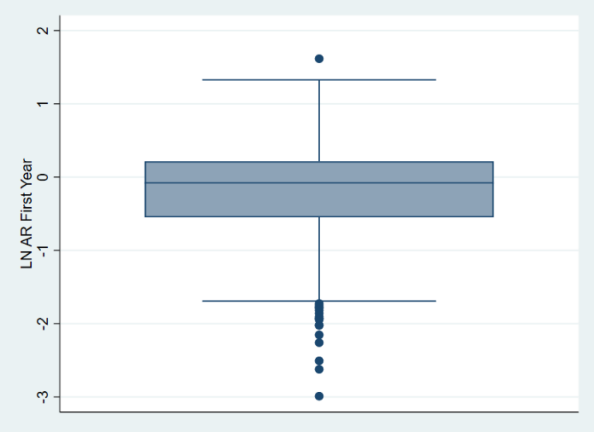

Figure 8 – Box-plot of the long-run log-transformed abnormal return.

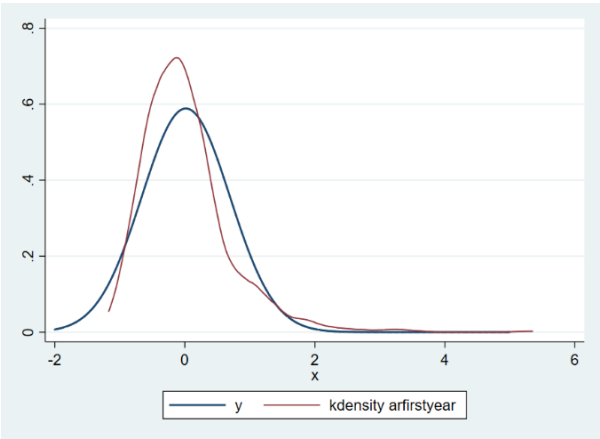

Figure 9 – Kernel density and normal distribution of the long-run abnormal. Bandwidth for the Kernel distribution: 0.1894.

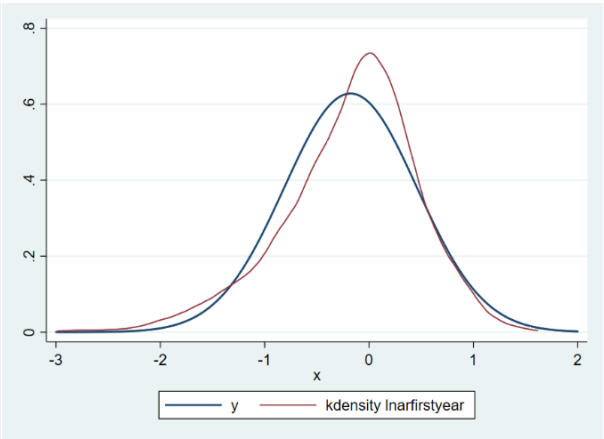

Figure 10 – Kernel density and normal distribution of the long-run log-transformed abnormal. Bandwidth for the Kernel distribution: 0.1776.

7.2 Appendix B: Output from statistical tests

Variables	**Bio-Tech.**	**Ln(Company Age)**	**Ln(ADJ Offer Size)**	**Ln(Pre-Listing Return)**	**VC**	**Under-writer**	**L.Q. Sent. (P.S.)**	**L.Q. Sent. (R.F.)**	**L.Q. Sent. M.D.A.**	**2003-2008**	**2008-2010**	**2010-2014**
Biotech.	1											
Ln(Company Age)	-0.170	1										
Ln(ADJ Offer Size)	-0.108	0.108	1									
Ln(Pre-Listing Return)	-0.006	0.023	0.008	1								
VC	0.175	-0.212	0.005	0.002	1							
Underwriter	-0.044	-0.084	0.395	0.012	0.149	1						
L.Q. Sent. (P.S.)	0.036	-0.028	-0.109	0.015	-0.003	-0.092	1					
L.Q. Sent. (R.F.)	-0.138	0.077	0.054	0.017	-0.118	-0.020	0.033	1				
L.Q. Sent. (M.D.A.)	-0.025	0.094	0.024	-0.031	-0.142	-0.044	0.101	0.074	1			
2003-2008	-0.148	0.009	0.062	-0.042	-0.265	0.016	0.039	-0.048	0.076	1		
2008-2010	-0.049	0.109	0.063	-0.114	-0.060	0.024	-0.005	0.012	-0.021	-0.132	1	
2010-2014	0.055	-0.001	0.100	0.154	0.174	0.079	-0.068	0.014	-0.102	-0.419	-0.105	1

Table 10 – Correlation matrix for all independent variables. No correlation higher than 0.8 indicates that there is no evidence of severe problems with multicollinearity.

Variables	VIF
Biotechnology	1.10
Company Age	1.11
ADJ Offer Size	1.26
Pre-Listing Return	1.04
VC	1.21
Underwriter	1.24
LQ Sent. (P.S.)	1.03
LQ Sent. (R.F.)	1.05
LQ Sent. (M.D.A)	1.05
2003-2008	1.39
2008-2010	1.10
2010-2014	1.32
Mean VIF	1.16

Table 11 - Variance inflation indicator (VIF). No VIF-value larger than 10 indicates no evidence of severe multicollinearity.

Log AR short-run	Coefficient	Probability
SQ Company Age	-0.006	0.292
SQ ADJ Offer Size	-0.011	0.013**
SQ Pre-Listing Return	-0.051	0.95

* p < 0.1, ** p < 0.05, *** p < 0.01

Table 12 – Squared terms in the short-run. Significant result for the squared term of the adjusted offer size indicates possible non-linearity.

Log AR long-run	Coefficient	Probability
SQ Company Age	0.030	0.119
SQ ADJ Offer Size	-0.044	0.001***
SQ Pre-Listing Return	-0.101	0.971

* p < 0.1, ** p < 0.05, *** p < 0.01

Table 13 – Squared terms in the long-run. Significant result for the squared term of the adjusted offer size indicates possible non-linearity.