BI Norwegian Business School - campus Oslo

GRA 19703

Master Thesis

Thesis Master of Science

Underpricing and Long-Run Performance of FinTech IPOs

Navn: Henrik Hystad Hove, Anders Flaglien

Start: 15.01.2019 09.00

Finish: 01.07.2019 12.00

Anders Flaglien

Henrik Aleksander Hystad Hove

Underpricing and Long-Run Performance of FinTech IPOs

Date of submission: 30.06.2019

Deadline: 01.07.2019

Campus: BI Oslo

Examination code and name: GRA19703 - Master Thesis

Programme: Master of Science in Business, Major in Finance

Supervisor: Kjell Jørgensen

Abstract

This thesis investigates the short- and long-run performance of 70 US FinTech IPOs issued between 2008 and 2018. We find that, during this period, FinTech IPOs experienced an average underpricing of 23%, which is significantly higher relative to the overall IPO market in the US in the same period (10.7%). We also find that venture capital backing has a significant positive effect on underpricing of FinTech IPOs. Moreover, high IPO activity seems to have a negative impact on the level of underpricing. In the long-run perspective, our findings indicate that FinTech IPOs experience positive abnormal returns, which is in contrast to most previous research. However, the long-run results are not statistically significant at an acceptable level and could be explained by randomness alone. Additionally, the results show that FinTech IPOs listed during a high IPO volume period have a negative effect on long-run performance.

Keywords: FinTech, IPOs, underpricing, long-run abnormal returns

Table of Contents

List of Tables

List of Figures

1. Introduction and motivation

1.1 Introduction

After the financial crisis of 2008, financial technology (FinTech) companies emerged at a high rate. These companies, which can be either startups or established IT companies entering the financial domain, have disrupted the financial industry with innovative products and services (Gomber, Koch, & Siering, 2017). As FinTech companies are focusing more on innovation, compared to traditional financial institutions, they are able to introduce new products and services at a higher rate (Gomber et al., 2017). However, the number of obstacles these companies must overcome are many, such as ongoing regulations and the demand for bank licenses (Gomber et al., 2017). Furthermore, a large number of FinTech companies are young startups, which entails dependence on funding from outside investors to enable further expansion of their business. One approach to overcome this challenge is to offer shares in the company to the public, which requires an initial public offering (IPO). In this way, FinTech companies can raise capital from public investors.

However, previous research shows that IPOs of operating companies are underpriced, on average (Ritter & Welch, 2002). Thus, the IPOs 'leaves money on the table' which could have raised more capital to the issuing firms if the offerings were priced more accurately. Scholars argue that uncertainty related to the IPO could explain why some IPOs experience underpricing (e.g., Ritter, 1984; Rock, 1986; Beatty & Ritter, 1986). Moreover, Beatty and Ritter (1986) suggest that riskier issues should be more underpriced, on average, because investors are less willing to purchase shares with higher ex-ante uncertainty unless they receive a higher expected return.

Valuations of FinTech companies can be a difficult task. Similar to most technology companies, they typically have few tangible assets and limited earnings in their early years. Besides, the technology is rapidly evolving and the regulations within the sector are increasing, which can make it difficult for FinTech companies to continuously keep up with the new technology and still comply to new regulations. This uncertainty makes it difficult for the issuing company and the underwriters when setting an initial price for the offering. Additionally, research suggests that technology companies experience greater underpricing than other industries (e.g., Karlis, 2008; Loughran & Ritter, 2004), likely as a result of the higher uncertainty related to these companies.

This thesis aims to examine whether FinTech IPOs experience underpricing, but also how they perform in the long-run. The long-run underperformance of new issues is another anomaly that has raised considerable interest among scholars. The main reason for this is because, like IPO underpricing, it is challenging the efficient market hypothesis (Ibbotson, Sindelar, & Ritter, 1994). Moreover, previous research indicates that underperformance is more significant among relatively young growth companies (Ritter, 1991), which suggests that FinTech companies could experience this anomaly.

1.2 Motivation

Most evidence on underpricing of technology IPOs is related to the Dot-com bubble. In this period, valuations of young tech companies were driven by high optimism related to their future earnings, resulting in high levels of underpricing. Technology companies amounted to 72% of the overall US IPO market during the peak of the bubble (1999–2000) and contributed significantly to the average underpricing in this period (Ritter & Welch, 2002). However, a large part of the technology sector has matured since the Dot-com bubble, resulting in more predictable future cash-flows. The FinTech sector, however, is still considered a rather new part of the technology industry. Thus, it is interesting to investigate whether FinTech companies experience some of the same traits as technology and Internet stocks experienced during the bubble period.

Previous research on IPO performance focus mostly on the overall IPO market, and few scholars concentrate on specific sectors. It is therefore of interest to investigate the FinTech sector, which has received significant attention among investors over the last ten years. Moreover, the FinTech sector has shown to be beneficial for a wide range of actors, even assisting the traditional banks in reaching out to untapped customer bases. Thus, FinTech companies have the potential to grow the financial market by including previously financially excluded firms and individuals. It is therefore of interest to investigate how the market reacts to IPOs from this sector, both in the short- and long-run.

1.3 Thesis structure

This thesis is divided into eight chapters. Chapter 2 presents a review of relevant literature regarding IPO underpricing and long-run performance. Chapter 3 establishes the FinTech terminology and explores the evolution of FinTech over the years. Furthermore, the main research question and the corresponding hypotheses are presented in chapter 4. A clarification of the methodology used is provided in chapter 5, and chapter 6 presents the data collection process and descriptive statistics. Chapter 7 shows the results and analysis, whereas chapter 8 outlines the conclusions and limitations of the thesis.

2. Literature review

IPO performance has been researched extensively throughout the years. This chapter will review relevant literature related to the underpricing and long-run performance of IPOs.

2.1 IPO underpricing

Ibbotson (1975) is one of the first authors to find empirical evidence of significant short-term underpricing during the 1960s for newly publicly issued firms. Later, numerous studies supporting these findings have been conducted. Ritter and Welch (2002) summarize that "approximately 70 percent of the IPOs end the first day of trading at a closing price greater than the offer price and about 16 percent have a first-day return of exactly zero" (p. 1802). Furthermore, they state that they know of no exceptions from the rule that IPOs of operating companies are underpriced, on average. This anomaly is challenging the efficient market hypothesis and has generated a large amount of literature (Ibbotson et al., 1994). In the following sub-chapters, relevant theories and empirical findings related to the underpricing of IPOs are presented. It is essential to accentuate that the theories presented are not mutually exclusive and may complement each other.

2.1.1 Information asymmetry

Most of the established theories on IPO underpricing are related to information asymmetry. The key participants in an IPO are the issuing firm, investors, and underwriters taking the firm public. When relevant information is not shared equally between these participants, some of the participants will be more informed than others, leading to information asymmetry. One of the first information asymmetry theories introduced was *the winner's curse model* by Rock (1986). This model argues that if the uninformed investors cannot know whether the equilibrium price of the shares reflects the true value or other factors, such as a change in risk aversion or liquidity needs, they will suffer the "winner's curse". This argument implies that the uninformed investors will only be allocated shares when the informed investors do not want them. Therefore, issuers must underprice their shares so that the uninformed investors expected initial return is positive, to ensure that they still participate in the IPO market (Clarkson & Merkley, 1994).

Beatty and Ritter (1986) extend the winner's curse model, arguing that "there is an equilibrium relationship between the expected underpricing of an initial public offering and the ex-ante uncertainty about its value" (p. 213). The rationale behind this proposition is that investors will not be willing to purchase shares with higher ex-ante uncertainty unless they receive a higher expected return through underpricing (Beatty & Ritter, 1986). For this to be true, riskier offerings must on average have a higher level of underpricing compared to less-risky offerings.

According to Clarkson and Merkley (1994), empirical tests of this model must rely on the use of proxies for ex-ante uncertainty. By investigating Canadian IPOs, they find evidence that higher ex-ante uncertainty results in a higher level of underpricing. Their results show that higher gross proceeds and underwriter prestige have a negative effect on underpricing. Furthermore, they find evidence of greater underpricing for firms classified as high-tech relative to firms in more regulated industries. Also, they document a significant positive relationship between the level of the market-based risk measures and underpricing. Similarly to Ritter (1984), they use the standard deviation of daily return in the aftermarket as a market-based risk measure.

2.1.2 Underwriter reputation

Beatty and Ritter (1986) were concerned with the question of why issuing firms do not take advantage of this underpricing phenomenon and sets the offering price too high instead of too low. They argue that, if issuing firms have no incentive to leave money on the table, outside investors could not in any way be assured that an issuing firm would leave money on the table. In this case, the IPO market might suffer the 'lemons' problem presented by Akerlof (1970). In a 'lemons' problem, investors are not able to separate "good" IPOs from "bad" IPOs, and only the issuer knows the difference. Beatty and Ritter (1986) argue that underwriters make it possible to overcome this problem because they have an incentive to offer IPOs at appropriate prices. Underwriters execute large numbers of IPOs over time and develop a reputation depending on their previous offerings. Because of this, it is in the underwriters' interest to enforce underpricing equilibrium as it improves their reputation (Beatty & Ritter, 1986).

Several studies find evidence of less underpricing for IPOs lead by more reputable underwriters (e.g., Carter & Manaster, 1990; Michaely & Shaw, 1994; Carter, Dark, & Singh, 1998). Furthermore, Nanda and Yun (1997) show that overpricing of IPOs negatively affect the market value of the lead underwriter (direct costs of the IPO taken into account), whereas moderate underpricing has the opposite effect on the underwriter's wealth.

2.1.3 Underwriter syndicates

Corwin and Schultz (2005) reveal that "employing more co-managers results in more accurate offer prices and possibly less underpricing if the initial filing price is set too low" (p. 443). They argue that managers of the issuing firm and the underwriters taking the firm public have different incentives. Because of this, the ratio of underwriters to managers could affect the level of underpricing. Moreover, they argue that as syndicate size increases, so does the accuracy of the offer price compared to actual market value, since a higher number of valuations and more diverse underwriters might be more representable of the market.

2.1.4 "Hot issue" markets

Ibbotson and Jaffe (1975) were the first to report cyclical patterns of initial returns, referred to as "hot issue" markets. They find that some periods during the 1960s experienced abnormally higher initial returns. Ritter (1984) supports these findings, reporting an average initial return of 48.4% during the 15 months between January 1980 and March 1981. In contrast, it was recorded an average underpricing of 16.3% during the rest of the 6-year period between 1977 and 1982 (Ritter, 1984). Moreover, the Dot-Com bubble was another "hot issue" period, in which it was reported an average IPO underpricing of 65% in 1999-2000 before reverting to 12% in 2001-2002 (Loughran & Ritter, 2004).

Loughran and Ritter (2004) try to explain the reason for the "hot issue" period during the Dot-Com bubble. They explore three possible explanations: changing risk composition, realignment of incentives, and changing issuer objective.

Changing risk composition

The hypothesis of changing risk composition argues that riskier IPOs should be more underpriced than less risky IPOs (Loughran & Ritter, 2004). Ritter (1984) is the first to introduce this hypothesis, arguing that "the hot issue market of 1980 was an equilibrium phenomenon explainable by (i) a positive equilibrium relation between risk and expected initial return and (ii) an increase in the riskiness of the average initial public offering" (p. 239). Thus, a higher portion of risky IPOs should result in higher average underpricing (Loughran & Ritter, 2004).

Their findings show that the risk composition did contribute somewhat to underpricing during the Dot-com bubble. From an OLS regression analysis, they find that assets and age had a negative effect on underpricing, whereas Internet and tech stocks had a positive effect on underpricing. These findings are consistent with the changing risk composition hypothesis. Thus, the fact that the Dot-com bubble saw a high number of young tech and Internet companies could explain part of the high level of underpricing (Loughran & Ritter, 2004).

Realignment of incentives

The realignment of incentives hypothesis, first introduced by Ljungqvist and Wilhelm (2003), argues that managerial incentives to reduce underpricing decreased during the tech bubble for various reasons (Loughran & Ritter, 2004). Some of the variables they tested were chief executive officer (CEO) ownership, ownership fragmentation, and shares allocated to friends and family. However, they find little evidence supporting this hypothesis. For example, CEO ownership was twice as high in 1999-2000 compared to the period 1996-1998, which should have reduced underpricing in this period (Loughran & Ritter, 2004).

Changing issuer objective

The last hypothesis, changing issuer objective, assumes that the issuers have become more willing to accept underpricing (Loughran & Ritter, 2004). The authors find evidence supporting this hypothesis, and came up with two hypotheses on why this is the case. First, *the analyst lust hypothesis* suggests that issuers had to pay for analyst coverage when choosing lead underwriters, which became more important during the bubble period, because the valuations were higher than in previous periods. Since the underwriters are unable to charge explicit fees for this, it is indirectly paid through underpricing. Second, *the spinning hypothesis* suggests that there is greater willingness to 'leave money on the table' by issuers because of the co-opting of decision-makers through side payments. In other words, venture capitalists and executives set up personal brokerage accounts where both benefit from receiving "hot IPOs", which in turn leads to an incentive to choose underwriters known for underpricing.

2.1.5 IPO volume

Ibbotson, Sindelar, and Ritter (1988) explain that following "hot issue" periods "there tend to be periods of "heavy" volume accompanied by relatively low initial returns (and thus less underpricing)" (p. 37). Furthermore, they argue that IPOs should be issued during high volume periods that follow the “hot issue” periods as the market is willing to pay high multiples for new issues. Lowry and Schwert (2002) support these findings, reporting cyclical patterns where IPO volume is higher following periods of higher levels of IPO underpricing. They argue that “it is information learned during the registration period that is positively related to future IPO volume” (p. 1199). Because the issuing companies use the information on the market’s valuations, they should want to issue their IPO when valuations are high, which suggests higher IPO volume and less underpricing in these periods (Lowry & Schwert, 2002).

2.1.6 IPO sponsorships

Lee and Wahal (2004) examine how venture capital (VC) backing affects the underpricing of IPOs. They find that VC backed IPOs between 1980-2000 experience greater underpricing compared to non-VC backed IPOs. Their result shows that the average return difference between VC backed and non-VC backed IPOs in this period ranges from 5.01% to 10.32%. Firms taken public by venture capitalists are generally smaller and younger firms with lower revenues than non-VC backed IPOs, which might explain these results (Lee & Wahal, 2004).

Furthermore, Lee and Wahal’s (2004) findings are in line with the grandstanding hypothesis proposed by Gompers (1996). The grandstanding hypothesis proposes that “(…) young venture capital firms take companies public earlier than older venture capital firms in order to establish a reputation and successfully raise capital for new funds” (Gompers, 1996, p. 133). Moreover, Gompers (1996) argues that “young venture capital firms have incentives to grandstand, i.e., they take actions that signal their ability to potential investors” (p.134).

For private equity (PE) backed IPOs, research indicate that these IPOs experience less underpricing compared to VC backed and non-sponsored IPOs. Levis (2011) finds that PE-backed IPOs were not affected by the “hot-issue” period during the Dot-com bubble. Furthermore, Bergström, Nilsson, and Wahlberg (2006) support these findings, using IPO data from Europe. They argue that it could be the case that PE-backing gives credit to the issuing firm since PE firms usually refrain from investing in “low quality” firms. This could stimulate reduced costly information gathering among investors, which in turn reduces the need for compensation by underpricing. Moreover, as private equity firms typically invest in more mature and stable firms, the lower levels of underpricing could reflect the riskiness of the issue, as previously discussed.

2.1.7 Underpricing of technology companies

As previously discussed, the high number of young tech and Internet companies going public during the Dot-com bubble could partly explain the high level of underpricing in this period (Loughran & Ritter, 2004). Karlis (2008) further supports this evidence, reporting a higher level of underpricing for Internet stocks compared to more established industries. The author explains that this is "mainly because investment banks are more uncertain of the value of Internet companies and subsequently underprice them to minimize the downside risk if the stock is overvalued and the issue is under subscribed" (p. 88). Furthermore, Karlis (2008) argues that companies with exceptionally high value have fewer reasons to underprice their issues because of the high demand from informed investors, which could explain why technology stock experience higher levels of underpricing. Because technology offerings are often too small for large institutional investors, and the fact that there is little historical information about these companies, they need to underprice in order to increase demand (Karlis, 2008).

2.2 Long-run performance of IPOs

While there has been extensive empirical evidence for the short-term underpricing of IPOs, research on the long-run perspective seems to point towards underperformance of new issues. Ritter (1991) is among the first to identify this trend. He finds that, over a 3-year holding period, issuing firms in the US between 1975 and 1984 underperformed compared to a sample of comparable firms in terms of size and industry. Moreover, Ritter (1991) argues that these findings are consistent with an IPO market where "(1) investors are periodically over optimistic about the earnings potential of young growth companies, and (2) that firms take advantage of these "windows of opportunity"" (p. 3). Loughran and Ritter (1995) support these findings, reporting poor subsequent 5-year performance of IPOs listed during the period 1970-1990, using the cumulative abnormal return (CAR) and buy-and-hold abnormal return (BHAR) as a measure. In the following sub-chapters, empirical findings on this long-run anomaly are presented.

2.2.1 Underwriter quality

Carter et al. (1998) find that the long-run returns relative to the market over a three-year holding period are less negative for IPOs handled by more prestigious underwriters. Moreover, Dong, Michel, and Pandes (2011) find that the quality of underwriters, measured by the number of underwriters, their reputation, and absolute price adjustment has a positive effect on the long-run performance of the IPOs. They argue that an IPO syndicate with a higher number of unique underwriters are more representable of the diverse actual market, and thus perform better in the long-run.

2.2.2 IPO volume

Ritter (1991) identifies that offerings issued during high-volume years' experience considerably more underperformance than those offered during low-volume years. Schultz (2003) support these findings and comes up with a possible explanation called the *pseudo market timing hypothesis*. This hypothesis suggests that more firms issue equity when prices increase and that managers predicted future returns have nothing to do with it (Schultz, 2003). Schultz (2003) argues that "firms could issue more equity at higher prices because higher prices imply more investment opportunities and firms go public to take projects" (p. 485). Moreover, he suggests that "offerings should cluster when stock prices are particularly high, and returns should be particularly poor following periods of heavy issuance" (p. 484).

2.2.3 IPO sponsorships

Brav and Gompers (1997) find evidence of higher long-run performance for VC-backed IPOs, compared to non-sponsored IPOs during a 5-year period between 1972 and 1992. Also, they find that VC-backed IPOs does not significantly underperform during this period. However, Gompers and Lerner (1998) find evidence of venture capitalists timing their transactions based on inside information. Their study show that sales by venture capitalists happened at around the same time as substantial run-ups in share value. As time progresses, the overly optimistic stock price then falls, and the IPOs underperformed on average (Gompers & Lerner, 1998). Thus, the literature on VC-backing is not set on any dominant findings concerning the long-run performance of VC-backed IPOs.

For PE-backed IPOs, on the other hand, the evidence seems to be more dominant towards overperformance, relative to other IPOs (e.g., Levis, 2011). This finding is in line with Jensen's (1986) theory on the free cash flow problem and the key value drivers of PE-backing. The theory states that a leveraged buyout decreases the agency cost of managers distributing free cash flows based on their self-interest and not in the interest of shareholders.

2.2.4 Underpricing and Long-Run performance

The relationship between IPO underpricing and long-run performance seems to have little empirical evidence, and different studies document contrasting results. For example, Ritter (1991) finds a negative relationship between underpricing and long-run performance, whereas Krigman, Shaw, and Womack (1999) reveals a positive relationship. Moreover, Ljungqvist, Nanda, and Singh (2006) find that the relationship is not necessarily monotonic, and the relation is negative only if the probability of the hot market ending is small.

3. Industry overview

To establish a conceptual foundation for the following chapters, this chapter explain the term FinTech and explores the evolution of FinTech over the years.

3.1 Terminology

In general, «FinTech» or «Financial Technology» can be explained as the use of technology to deliver financial solutions (Arner, Barberis, & Buckley, 2016). According to Gomber et al. (2017) "FinTech refers to innovators and disruptors in the financial sector that make use of the availability of ubiquitous communication, specifically via the Internet and automated information processing" (p. 540). However, Lee (2015) differentiates between established financial services using FinTech to protect their market position and new companies who offer financial products and services, challenging the traditional financial companies. The latter, which can either be start-ups or established IT companies entering the financial domain, are referred to as FinTech companies (Gomber et al., 2017).

3.2 The evolution of FinTech

Arner et al. (2016) distinguish between three eras of FinTech: FinTech 1.0 (1866-1967), FinTech 2.0 (1967-2008), and FinTech 3.0 (2008- present). The first era of FinTech started when technologies such as the telegraph, railroads, canals, and steamships were invented. These technologies made interconnections across borders possible, allowing rapid transmission of financial information, transactions, and payments around the world (Arner et al., 2016). After World War 1, the development of financial technology further improved with firms transitioning codebreaking tools into early computers, and in the 1950s banks introduced the first credit cards, which later became a global consumer revolution (Arner et al., 2016).

The modern evolution of FinTech started with the introduction of the Automatic Teller Machine (ATM) in 1967 (Arner et al., 2016), marking the start of Fintech 2.0. In this era of FinTech, the financial industry went from being analog to digital. By the late 1980s, financial services had developed into a digital industry which relied on electronic transactions between financial institutions, financial market participants, and customers around the world (Arner et al., 2016). The development of the Internet made transactions and payments over long distances possible. The Internet also sat the stage for the next level of development when Wells Fargo began using the World Wide Web (WWW) to provide online consumer banking (Arner et al., 2016). As a result, banks were able to communicate with consumers more efficiently.

In the aftermath of the financial crisis in 2008, a shift in the financial industry occurred. The crisis made people more skeptical toward traditional banks, which led to a more positive view towards new and innovative financial solutions from FinTech start-ups and IT-companies (Arner et al., 2016). Moreover, people in the developing world became more willing to place their money into platforms that were provided by non-bank companies due to cheaper cost and increased convenience (Arner et al., 2016). As technology has improved substantially over the last ten years, and the fact that people have become more willing to adopt technology, FinTech companies are experiencing exponential market-based growth. Today, the FinTech landscape, in which these companies operate within, consists of a broad range of different segments. Some of these are digital money, mobile payments, peer-to-peer (P2P) lending, smart contracts, open banking, insurance technology (InsurTech), regulatory technology (RegTech), wealth management (WealthTech), and robo-advisors.

4. Research question and hypotheses

This chapter first presents the main research question of this thesis. Then, based on previous literature on IPO underpricing and long-run performance, hypotheses to be tested are presented.

4.1 Research question

The objective of this thesis is to examine whether FinTech IPOs in the US are underpriced and how they perform in the long-run. Hence, our main research question is:

How does FinTech IPOs in the US perform in the short- and long-run?

4.2 Research hypotheses

4.2.1 Underpricing hypotheses

Previous literature shows that IPOs in the US experience significant underpricing. Even though the level of underpricing seems to vary among different industries, the conclusion has been that IPOs as a group are underpriced on average (Ritter & Welch, 2002). Therefore, our first hypothesis is:

Hypothesis 1: *All IPOs in total experience a significant positive level of underpricing.*

The technology industry has shown to experience higher levels of underpricing, compared most other industries (Karlis, 2008). Since FinTech companies operate within the technology sector, one should assume that these companies experience a higher degree of underpricing relative to the rest of the IPO market. Thus, our second hypothesis is:

Hypothesis 2: *FinTech IPOs experience significantly higher underpricing compared to all IPOs in total.*

Previous research identify a number of factors that can affect the level of underpricing. One of these factors is the reputation of the lead underwriter. As underwriters develop a reputation depending on their previous offerings, they are incentivized to limit underpricing in order to improve their reputation (Beatty &

Ritter, 1986). One should therefore expect that higher underwriter reputation has a negative effect on underpricing. Based on this rationale, our third hypothesis is:

Hypothesis 3: *Higher level of underwriter reputation has a significant negative effect on the underpricing of FinTech IPOs.*

Another factor that could affect the level of underpricing is related to the period the offering was issued. Previous research indicates that IPOs listed during periods of high IPO activity experience lower level of underpricing (e.g., Ibbotson et. at, 1988; Lowry & Schwert, 2002). For our fourth hypothesis, we therefore want to test whether high IPO activity affects the level of underpricing negatively.

Hypothesis 4: *High IPO activity has a significant negative effect on the underpricing of FinTech IPOs.*

Moreover, research by Lee and Wahal (2004) indicate that firms taken public by venture capitalists experience higher levels of underpricing. For our last underpricing hypothesis, we therefore want to test how VC backing affects the underpricing of FinTech IPOs.

Hypothesis 5: *VC backing has a significant positive effect on the underpricing of FinTech IPOs.*

4.2.2 Long-run performance hypotheses

In the long-run perspective, the research points towards underperformance, and the pattern is most significant for young growth companies (Ritter, 1991). As FinTech companies often are classified as young growth companies, our sixth hypothesis tests whether these IPOs experiences this anomaly:

Hypothesis 6: *FinTech IPOs experience significant underperformance in the long-run.*

There is evidence indicating that IPOs lead by underwriter syndicate with a higher number of unique underwriters perform better in the long-run, as they could be more representable of the diverse actual market (Dong et al., 2011)). Our seventh hypothesis is therefore:

Hypothesis 7: *A higher number of unique underwriters have a significant positive effect on long-run performance of FinTech IPOs.*

Research also indicates that companies going public during high-volume years' experience considerable long-run underperformance (e.g., Ritter, 1991; Schultz, 2003). Thus, we form our last hypothesis:

Hypothesis 8: *High IPO activity has a significant negative effect on long-run performance of FinTech IPOs.*

5. Methodology

This chapter presents the methodology used when answering our research question and hypothesis.

5.1 Underpricing

5.1.1 Initial returns

When calculating initial returns, it is necessary to first establish the length of the time period following the initial offering to be used. Some of the older research on underpricing use more extended time periods when calculating initial returns (e.g., Ibbotson, 1975), mainly because daily stock prices were less available prior to the development of Nasdaq (Ibbotson et al., 1994). However, as daily returns have become more available, most recent studies have focused on first-day returns. Hence, we calculate initial returns as follows:

$$R_i = \frac{P_i}{O_i} - 1$$

Where R_i is the first-day return of firm i, P_i is the closing price of the issue on the first trading day, and O_i is the offer price of the issue.

First-day closing price is used because the majority, and most recent literature, measures underpricing by the first-day closing price (e.g., Loughran & Ritter, 2004; Lowry & Schwert, 2002), rather than the bid- or average between bid and ask prices (e.g., Ritter, 1984; Beatty & Ritter, 1986). It is worth noting that initial returns are not adjusted for same day market returns, as we expect these on average to be significantly lower than the IPO returns, which is in conjunction with previous literature (e.g., Beatty & Ritter, 1986).

When calculating the average first-day return of all IPOs, and for the sample of FinTech IPOs, all firms are equally-weighted. In other words, smaller firms have the same weight as larger firms. The equally weighted average first-day return for each sample is calculated as follows:

$$R_s^{ew} = \frac{1}{n_s}\sum_{i=1}^{n_s} \mathrm{R_i}$$

Where R_s^{ew} is the equally weighted first-day return of sample s, n_s is the number of IPOs in sample s, and R_i is the first-day return of firm i.

5.1.2 Statistical hypothesis testing

To test Hypotheses 1 and 2, mean difference t-tests are used. First, we test whether all IPOs in total experience significant positive levels of underpricing (Hypothesis 1). This hypothesis is tested by using a one-sample t-test of whether the first-day returns are statistically significantly different from zero. Second, we test whether FinTech IPOs experience significantly higher underpricing compared to all IPOs in total (Hypothesis 2). This hypothesis is tested using a two-sample t-test of whether the difference between the two samples is statistically significantly different from zero.

5.1.3 Multivariate regression model

A multivariate OLS regression analysis is used to test Hypothesis 3, 4, and 5. The independent variables included in the model are underwriter reputation (UnderwriterReputation), a dummy variable expressing whether the IPO was issued during a high IPO activity period (HAPDummy), and a dummy variable stating whether the issuing company was VC backed (VCDummy). Moreover, the size of the offering (LN(proceeds)), the number of underwriters (NumberOfUnderwriters), and a dummy variable stating whether the issuing company was PE backed (PEDummy) is included in the model. Also, the standard deviation of daily returns (StdDev49) is used as a market-based risk measure variable. The reason for including all these variables is because they have shown an effect on underpricing in previous research. Thus, we are reasonably certain that our model does not have an omitted variable bias problem.

Using first-day returns of FinTech IPOs (FirstDayReturn) as the dependent variable, the following regression model is formed:

$$FirstDayReturn_i = \alpha_i + \beta_1 UnderwriterReputation_i + \beta_2 HAPDummy_i$$
$$+ \beta_3 VCDummy_i + \beta_4 PEBackedDummy_i + \beta_4 \ln(Proceeds)_i$$
$$+ \beta_5 NumberOfUnderwriters_i + \beta_7 StdDev49 + \varepsilon_i$$

The model uses White's heteroskedasticity consistent standard errors to account for any heteroskedasticity in the variance of the errors. Moreover, we check for multicollinearity through a correlation matrix of the variables. Table 5.1 contains a short explanation of each variable and its expected impact on underpricing.

Table 5. 1 Regression variables

Variable	**Explanation**	**Expected effect on underpricing**
FirstDayReturn	First day return of FinTech IPOs, calculated as percentage change between IPO offering price and closing price at the end of the first trading day.	Dependent variable
UnderwriterReputation	Ranking from 0-9 based on the lead underwritters level of reputation	Negative
HAPDummy	Companies whose offering occured during a period of high IPO activity.	Negative
VCDummy	Companies backed by venture capital when going public.	Positive
PEDummy	Companies backed by private equity when going public.	Negative
LN(Proceeds)	The natural logarithm of the total amount raised from the IPO.	Negative
NumberOfUnderwriters	The total number of underwriters participating in the offering.	Negative
StdDev49	Standard deviation of daily returns measured over the 49 trading days after the first day of trading.	Positive

5.2 Long-run performance

According to Schultz (2003), most of the empirical work on long-run performance is based on event time returns. This technique simulates investing equal amounts of money in each offering and calculates the abnormal performance following each offering (Schultz, 2003). An alternative way to measure long term performance is by using calendar time returns. When using this technique, each month is weighted equally, even though the offerings cluster in time (Schultz, 2003). As a result, IPOs in low volume periods are weighted heavier, compared to IPOs listed during high volume periods. In our study, we use event time returns, which has previously shown to result in more substantial underperformance (Schultz, 2003).

5.2.1 Abnormal returns in event time

Previous research related to long-run IPO performance provide several arguments as to which measures are optimal in order to capture the true abnormal returns. The conventional methods used to calculate this is cumulative abnormal return (CAR) and buy-and-hold abnormal returns (BHAR) (Barber & Lyon, 1997). Similar to

Ritter (1991), we use 21 trading days per month and calculate the performance following the first-day closing price, which to some degree is independent of the offer price. The closing price is used because there are limitations as to whether an investor can invest at the offer price, contrary to the first-day closing price which is more publicly available (Loughran & Ritter, 1995).
The CARs and BHARs are calculated in the following way:

$$\mathrm{CAR_i} = \sum_{t=1}^{T} (\mathrm{r_{i,t}} - r_{b,t})$$

Where CAR_i is the cumulative abnormal return of stock i, T is the total number of seasoning months, $r_{i,t}$ is the return of stock i at time t and $r_{b,t}$ is the return of the benchmark index at time t.

$$BHAR_i = \prod_{t=1}^{T} (1 + r_{i,t}) - \prod_{t=1}^{T} (1 + r_{b,t})$$

Where $BHAR_i$ is the buy-and-hold abnormal return of stock i in the period t-T, T is the total number of seasoning months, $r_{i,t}$ is the return of stock i at time t, and $r_{b,t}$ is the return of the benchmark in the same period.

The CAR measure assumes a rebalancing of the portfolio each month, in which delisted stocks are removed, and gains or losses are put into the new rebalanced portfolio (Ritter, 1991). The BHAR measure, on the other hand, calculates the return from buying the stock at the closing price of the first day of trading and holding it until the stock is either delisted or the time period has passed (Ritter, 1991). The CAR measure also ignores the compounding effect of holding the stock, which makes the two measures proportionally different as the time period of measurement increases (Barber & Lyon, 1997). Furthermore, since the CAR metric assumes periodically rebalancing of the portfolio, it could be argued that it is not a realistic measure as frequent trading leads to high transactional costs. On the other hand, Fama (1998) argues that since the BHAR metric is skewed (because of its compounding nature), the CAR metric is better suited for measuring long-run performance.

5.2.2 Statistical hypothesis testing

When testing whether FinTech IPOs experience significant underperformance in the long-run (Hypothesis 6), we use two different statistical tests. Because the BHARs are not assumed to be normally distributed, relying solely on a t-test when testing this distribution can be insufficient. Thus, we also perform a one-sample sign test on BHARs, which tests whether the distribution has a median of zero. CARs, on the other hand, are assumed to be normally distributed. Hence, we perform mean difference t-tests to test whether the CARs are significantly different from zero for each seasoning month.

5.2.3 Multivariate regression model

In order to test Hypothesis 7 and 8, we form two separate regression models, using 3-year CAR and BHAR as dependent variables in each model. The same explanatory variables as in the underpricing model are used. However, we also include first day returns (FirstDayReturn) as an independent variable to test its effect on long-run performance.

Model 1:

$$3yearCAR_i \; = \; \alpha_i + \beta_1 UnderwriterReputation_i + \beta_2 HAPDummy_i$$
$$+ \beta_3 VCDummy_i \;\; + \beta_4 PEBackedDummy_i \;\; + \beta_4 \ln(Proceeds)_i$$
$$+ \;\; \beta_5 NumberOfUnderwriters_i \;\; + \beta_7 StdDev49 + \beta_8 FirstDayReturn_i + \varepsilon_i$$

Model 2:

$$3yearBHAR_i \; = \; \alpha_i + \beta_1 UnderwriterReputation_i + \beta_2 HAPDummy_i$$
$$+ \beta_3 VCDummy_i + \beta_4 PEBackedDummy_i + \beta_4 ln(Proceeds)_i$$
$$+ \beta_5 NumberOfUnderwriters_i \;\; + \beta_7 StdDev49 + \beta_8 FirstDayReturn_i + \varepsilon_i$$

Similar to the underpricing regression model, we use White's heteroskedasticity consistent standard errors in both models, and check for multicollinearity through a correlation matrix of the variables.

6. Data and descriptive statistics

In this chapter, the data collection process is outlined, including the construction of variables used in the multivariate regression models. Moreover, descriptive statistics summarizing parts of the dataset is presented throughout the chapter. An evaluation of the data quality is provided at the end of the chapter.

6.1 Initial sample generation

In the initial data sample generation, a list of all IPOs in the US was acquired from the SDC Platinum database from Thomson Financial. Considering the era of FinTech 3.0 emerged after the financial crisis of 2008, the dataset is restricted to IPOs from 2008 until the end of 2018. The initial list contained information about the name of the issuing company, the IPOs issue date, offer price, and first-day closing price. It is worth mentioning that we included penny stocks (offer value less than $5) in the dataset. According to Ibbotson et al. (1988), including these may affect the calculation of equally-weighted average initial return as they have previously shown to increase underpricing significantly. However, the penny stocks seem to have little impact on the average underpricing in this dataset, as illustrated in appendix 4, which is why we decided to include them.

We also excluded subsidiaries and stocks that have previously been listed from the dataset. An example is PayPal which went public for the second time in 2015, operating as a wholly owned subsidiary of eBay. Furthermore, extreme outliers of underpricing, which seem to have been adjusted incorrectly or merged with other companies, were removed from the dataset. After excluding these IPOs, we ended up with 1519 IPOs. However, in 380 of the 1519 IPOs, the first-day closing prices were missing from the SDC Platinum database. As a consequence, these were removed from the dataset, leaving 1139 IPOs in total.

6.2 Mapping of FinTech IPOs

After the initial data generation, newly issued firms regarded as FinTech companies were manually mapped out. This process was done mainly by using the different FinTech indices: KBW Nasdaq Financial Technology Index, Stoxx Global Fintech Index, and The CedarIBS FinTech Index. In addition, Financial Technology Partners (2019) provided some information about US Fintech companies going public over the years. After mapping all possible FinTech IPOs, we cross-checked against prospectuses where these were obtainable to make sure the IPOs fit the

FinTech category. As seen in Table 6.1, the final list contains 70 FinTech IPOs out of the 1139 IPOs in total.

Table 6. 1 Distribution of Initial Public Offerings

	Number of IPOs		Proceeds ($ millions)		Underpricing	
Year	*All IPOs*	*Fintech IPOs*	*All IPOs*	*Fintech IPOs*	*All IPOs*	*Fintech IPOs*
2008	31	2	25 472	18 109	3.1 %	32.1 %
2009	28	2	17 328	1 964	15.6 %	22.6 %
2010	61	9	39 959	1 231	6.2 %	16.3 %
2011	38	3	36 711	864	12.7 %	21.7 %
2012	104	7	49 190	1 144	10.0 %	38.1 %
2013	222	3	62 182	360	11.8 %	19.1 %
2014	207	16	51 356	7 081	11.4 %	16.5 %
2015	132	7	25 215	4 556	11.6 %	10.5 %
2016	66	4	12 056	664	11.5 %	33.9 %
2017	134	7	28 240	824	9.2 %	25.0 %
2018	116	10	30 947	3 028	10.8 %	31.6 %
Total	**1139**	**70**	**378 654**	**39 826**	**10.7 %**	**23.0 %**
Yearly Average	104	6	34 423	3 621	10.3 %	24.3 %
Yearly Median	104	7	30 947	1 231	11.4 %	22.6 %

6.3 Collection of IPO performance data

In the next step of the data collection process, the IPO performance of FinTech IPOs in our dataset was retrieved from Thomson Reuters Eikon Datastream using the Reuters Instrument Code (RIC) for each stock. From this database, time series data for each stock was provided from the first trading day until end of year 2018, or as long the stock was listed. Subsequently, we collected the closing price for the first trading day and closing prices at the end of every consecutive trading month for 3-years. As previously mentioned, each month consist of 21 trading days, as it is a close approximation of actual trading days per month.

We also cross-checked the first-day returns obtained from the SDC Platinum database, towards the data retrieved from Thomson Reuters Eikon Datastream. However, the offer and closing prices initially collected from SDC Platinum were unadjusted for any splits, dividends, and other capital changes. Because Thomson Reuters Eikon Datastream uses capital structure adjusted stock prices, the adjusted offer price was also collected from the SDC Platinum database. An example of capital structure change is Medidata Solutions Inc (MDSO). which had a 2 for 1 split in 2013. In our dataset, this change of capital structure is accounted for to make sure the underpricing is real and not a result of e.g. a stock split.

To compare the performance of FinTech IPOs against a suitable benchmark, we collected data on the NASDAQ composite index from Thomson Reuters Datastream. We chose not to use a pure FinTech index as a benchmark because these indices tend to contain a low number of stocks. For example, the KBW Nasdaq Financial Technology index contains only 48 stocks, and almost all of them are a part of our sample. As a consequence, the difference between the performance of our sample and a FinTech index would be too small to measure any significant difference.

6.4 Construction of regression variables

6.4.1 Underwriter reputation rank

The underwriter reputation measure is based on five criterions. Information used to evaluate each criterion was collected from the SDC Platinum database from Thomson Financial and Ritter (2015). The first two criteria are the number of times each underwriter acted as lead underwriter and the number of times they have been involved in a transaction over the last ten years. For the next two criteria, we collected the total proceeds for when each underwriter was the lead underwriter and the total proceeds when each underwriter was a part of the underwriting process. Then, we calculated the relative score within each of the four measurements mentioned earlier for each underwriter in the total sample. Furthermore, we assigned each underwriter a rank between 0 and 9 for each criterion and included a fifth criterion, which is the underwriters score assigned by Ritter (2015). The integer average of these five scores resulted in a score between 0 and 9 for each underwriter. The list over underwriters and their corresponding rankings can be found in Appendix 3.

6.4.2 IPO activity

To determine which IPOs that were issued during a high IPO activity period, we plotted the total number of IPOs offerings each year during the period from 2008-2018. As seen in Figure 6.1, the overall IPO market experienced significantly higher activity during the period 2013-2015. However, FinTech IPOs experienced a notable higher activity solely in 2014, and therefore 2014 is the only year classified as a high IPO activity period.

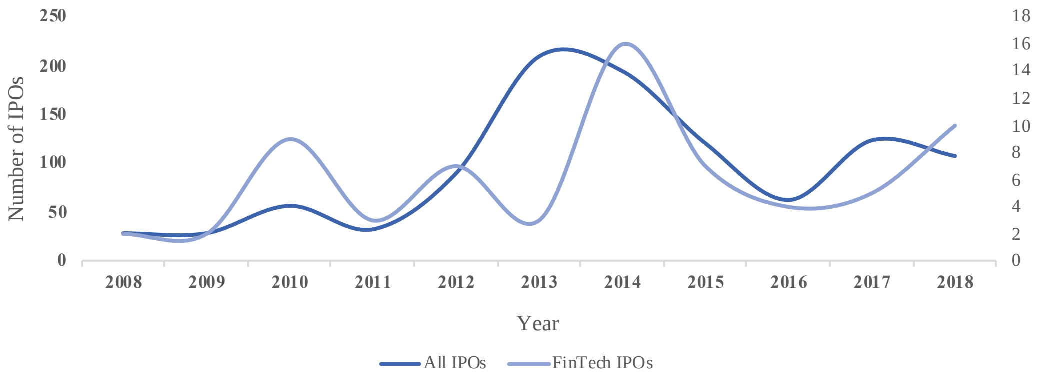

Figure 6. 1 Number of IPOs from 2008 to 2018. Left vertical axis displays number of IPOs in total sample, while the right axis displays number of IPOs in FinTech sample.

6.4.3 IPO sponsorships

Information about whether the IPO was VC backed, PE backed, or non-sponsored when the offering occurred was collected from the SDC Platinum database from Thomson Financial. An overview of the sponsorship composition is presented in Table 6.2. As seen from this table, the majority of the companies are VC backed. Appendix 2 presents information about which FinTech companies are VC backed, PE backed, or non-sponsored.

Table 6. 2 Sponsorship distribution

VC backed	41
PE backed	18
Non-sponsored	11
Sum	70

6.4.4 Number of underwriters

The deal specific number of underwriters was collected from SDC Platinum from Thomson Financial. This number represents the number of unique underwriting companies involved in each IPO, and should not be confused with the number of people involved in the issue. Appendix 1 provides information about the number of unique underwriters involved in each IPO. The average number of underwriter representations is 4 per deal.

6.4.5 Proceeds

The amount raised from each offering (proceeds) was collected from SDC Platinum database from Thomson Financial. However, for the variables to fit a linear model we use the natural logarithm (ln) of proceeds. Figure 6.2 and 6.3 presents the distribution of proceeds before and after logarithmically adjusting the variables.

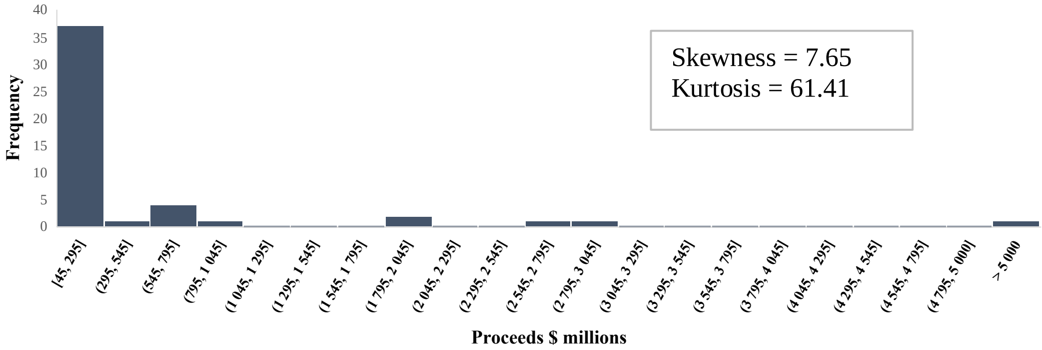

Figure 6. 2 Distribution of proceeds in each issue.

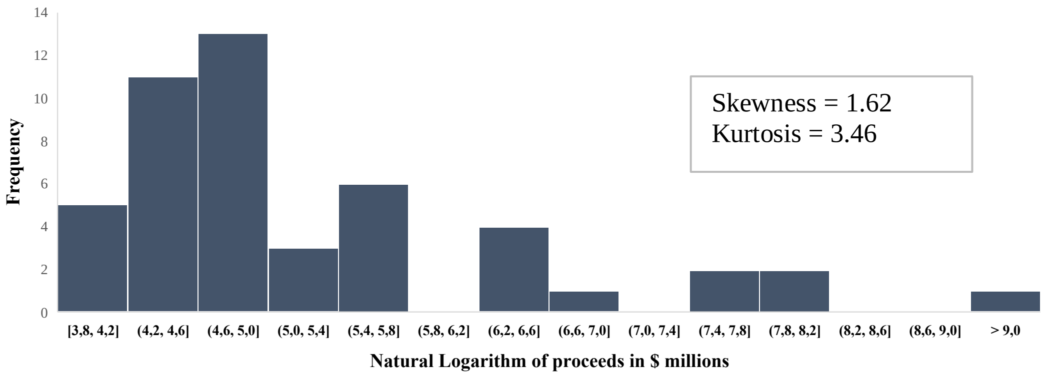

Figure 6. 3 Distribution of the natural logarithm of proceeds in each issue.

6.4.6 Standard deviation of returns

Consistent with Ritter (1984), we use the standard deviation of daily return in the aftermarket to measure its effect on ex-ante risk for each individual stock. To construct this variable, the standard deviation of the 49 consecutive trading days following the IPO was calculated. The number of days used in the calculation makes it possible to include almost all IPOs in the dataset. Only one FinTech IPO had to be removed as it was only listed for 13 trading days before it was taken of the market.

6.5 Data quality evaluation

The two data sources used when constructing the dataset are SDC Platinum from Thomson Financial and Thomson Reuters Eikon Datastream. We did not cross-check our data towards other data sources, such as Bloomberg or Dealogic, and we can therefore not be sure that all of the data is correct. For example, we could have checked whether the information regarding IPOs backing collected from SDC Platinum is correct, as there can be a fine line between VC and PE transactions. However, the data collection process was a time-consuming operation, and collecting data from more sources would most likely not be worthwhile.

The process of mapping FinTech IPOs was done manually and could therefore result in some errors. However, we did cross-check all FinTech IPOs in the dataset to be certain they fit the FinTech category, but there could still be companies we missed that fit the category. If some FinTech IPOs are missing, it may affect our results. However, the mapping process was performed thoroughly, and we therefore assume few errors.

Regarding the underwriter reputation score, there seem to be a few different approaches to this measure. Our approach is not necessarily a correct representation of how the underwriter is viewed to the responsible members of a deal. A more comprehensive measure could be done with a more qualitative measure, perhaps through interviews and scorecards gathered from managers.

7. Results and analysis

The following chapter presents and analyzes the underpricing and long-run performance results.

7.1 Underpricing results

7.1.1 Distribution of first-day returns

The distribution of first-day returns among all firms in our sample is positively skewed, with a skewness of 1.36 and kurtosis of 2.66. This distribution result is in conjunction with Ibbotson's (1975), which implies that an investor randomly drawing an IPO from this distribution has a higher chance of extremely high performance than a corresponding extremely low performance. Moreover, the median of first day returns is 3.00%, which is substantially lower than the mean (10.40%), implying that there is a relatively similar number of IPOs experiencing gains and losses. A Jarque-Bera test shows that the distribution is statistically significantly different from a normal distribution (p = .0010).

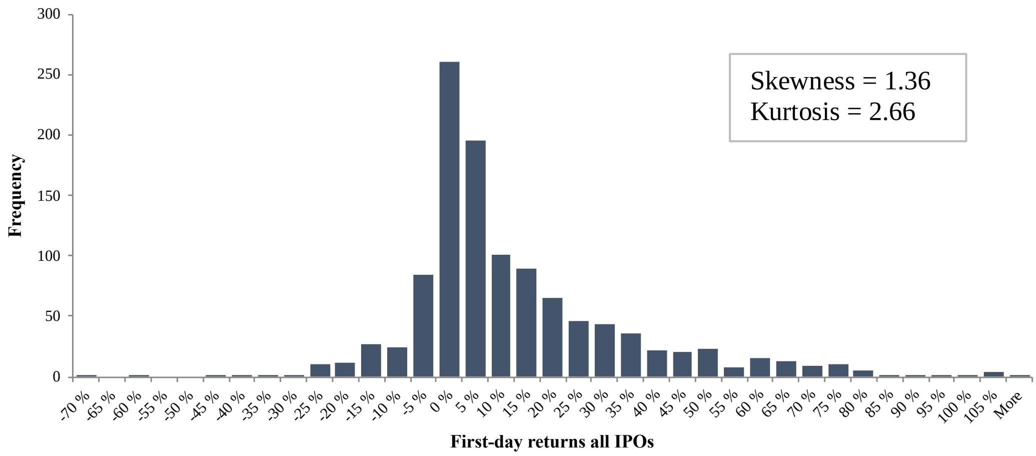

Figure 7. 1 Distribution of first-day returns in total IPO sample.

The distribution of first-day returns for FinTech IPOs (Figure 7.2) has a positive skewness of 0.62 and kurtosis of 0.71. Moreover, the median of first day returns is 19.00%, which is significantly higher than for all IPOs in total. This indicates that a large number of FinTech IPOs experience relatively high levels of underpricing. Furthermore, a Jarque-Bera test on the FinTech sample indicates that the distribution is non-normal (p = .0497).

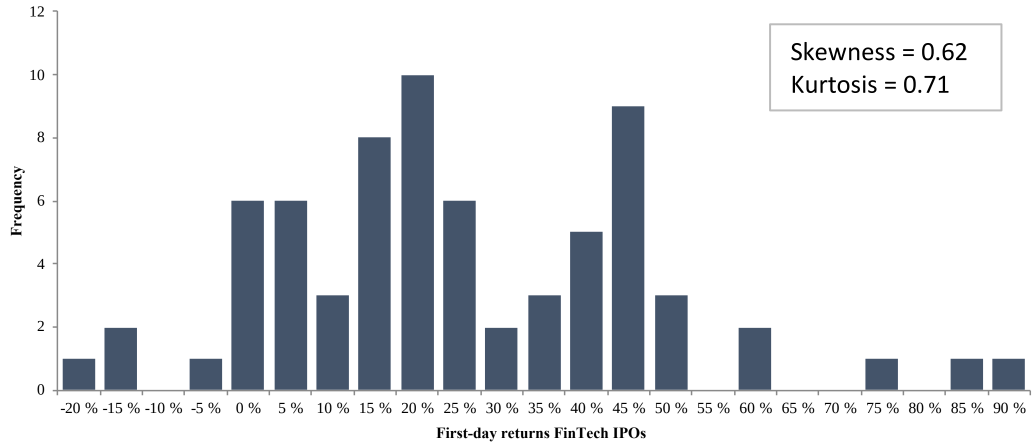

Figure 7. 2 Distribution of first-day returns in FinTech IPO sample.

Figure 7.3 provides a comparison between equally weighted average returns each year for FinTech IPOs and all IPOs in total. The results show that the underpricing of FinTech IPOs exceeds the underpricing of the total sample across all years except 2015. It is worth noting that the total sample of IPOs is highly stable from 2011 to 2018. This is not the case for FinTech IPOs, which are underpriced at noticeably different levels across different years. A possible explanation for this fluctuation is that it reflects the fact that FinTech is a relatively young sector when compared to the total sample, thus increasing the return-volatility of the sector.

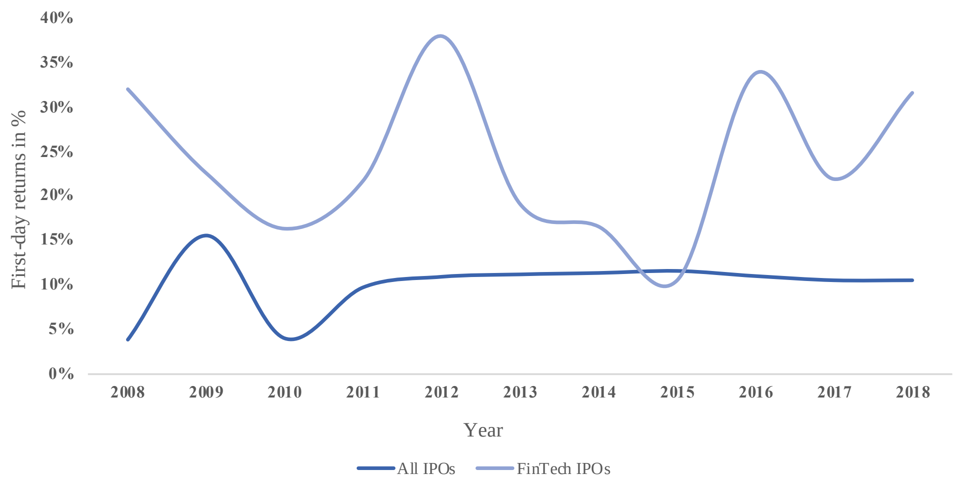

Figure 7. 3 Equally weighted average first-day returns

7.1.2 Statistical tests of first-day returns

As previously mentioned, mean difference t-tests are used to test whether the equal-weighted average first-day returns are statistically significantly different from zero. From these results, we can infer that there is evidence of statistically significant positive average first-day returns for all IPOs in total ($p < .001$). Thus, we find support for Hypothesis 1, stating that all IPOs in total experience a significant positive level of underpricing. Moreover, the mean underpricing of FinTech IPOs is also statistically significantly higher than for the total sample ($p < .001$). This result supports Hypothesis 2, stating that FinTech IPOs experience significantly higher underpricing compared to all IPOs in total. Table 7.1 presents the results from the mean difference t-tests on underpricing of all IPOs and the sub-sample of FinTech IPOs, as well as the mean and median of the two samples. Also, the table shows the results from the two-sample t-test, as well as the difference between the mean and median of the two samples.

These results indicate that FinTech IPOs are underpriced, and that they are more underpriced than the overall IPO market in the US, on aggregate Previous research suggest that technology companies experience a higher level of underpricing, relative to other industries, due to higher uncertainty related to these companies (e.g., Loughran & Ritter, 2004; Karlis, 2008). Thus, our findings are in line with this argument and previous findings on technology companies. Moreover, these results could indicate that FinTech companies raising capital through an equity offering might want to increase their offer prices in future IPOs. On the other hand, it can be a result of the uncertainty and early development stage of the sector. As previously discussed, risky IPOs are often underpriced to be more certain investors invest in similar companies in the future. Thus, the high level of underpricing could be a compensation for the riskiness of the FinTech sector.

Table 7.1 Mean difference t-tests of first-day returns

Sample	**Mean**	**T-statistic**	**P-value**	**Median**
All IPOs	10.70 %	16.5006	< 1.000e-3	2 %
FinTech IPOs	23.00 %	8.7404	8.8650e-13	19 %
Difference	12.30 %	3.8525	1.2451e04	17 %

7.1.3 Multivariate regression analysis

Table 7.2 displays the results from the multivariate OLS regression on underpricing, with the estimated coefficients from the set of explanatory variables previously presented. The first thing to note is that the model seems to explain a fair amount of the variability in underpricing, $\Delta R^2 = .34$, $F = 5.98$. The output from the regression model, presented in Table 7.2, shows that three of the total seven variables are statistically significant at a 5 % significance level, whereas two more variables are significant at a 10% significance level. Moreover, the correlation matrix (Appendix 1) reports that some of the variables correlate at a reasonably high level. More precisely, the number of underwriters and the size of the deal (proceeds), correlates positively (*Corr.* = .67). This could be explained by the fact that larger deals require a larger syndicate size.

The underwriter reputation coefficient is not statistically significant an acceptable level ($p = .6333$). Furthermore, the coefficient seems to have little effect on underpricing. Disregarding the significance and level of impact of this coefficient, the effect of it is negative on the level of underpricing, which is in line with previous research (e.g., Carter & Manaster, 1990; Michaely & Shaw, 1994; Carter et al., 1998). The result indicates that FinTech IPOs taken public by more reputable underwriters experience marginally, but insignificantly, less underpricing. However, since this coefficient is not significant at an acceptable level, we find no support for Hypothesis 3, stating that a higher level of underwriter reputation has a significant negative effect on underpricing of FinTech IPOs.

Regarding Hypothesis 4, there is a negative relationship between IPOs listed during high IPO activity period and underpricing. However, the coefficient is only statistically significant at a 10% significant level ($p = .0685$). This result is in line with previous research on IPO underpricing (e.g., Ibbotson et al., 1988; Lowry & Schwert, 2002), and indicates that FinTech IPOs issued during a period of high IPO volume experience less underpricing. Moreover, the results partly support Hypothesis 4, stating that high IPO activity has a significant negative effect on underpricing of FinTech IPOs.

The VC backed issue coefficient is statistically significant at a 1 % significance level ($p < .001$), and is estimated to affect underpricing positively in the model. VC backing seems to have a substantial effect on the level of underpricing, which is in line with previous research by Lee and Wahal (2004). This could be explained by the fact that venture capitalists typically invest in young firms with high-growth opportunities, and could therefore be more exposed to underpricing because of overoptimism among investors. Based on these results, we find support for Hypothesis 5, stating that VC backing has a significant positive effect on underpricing of FinTech IPOs.

The PE backed issue coefficient is significant at a 10% level ($p = .0978$) and has a positive effect on underpricing. Previous literature suggests a negative relationship between underpricing and PE sponsorship, which means that the estimate regarding this coefficient is in contrast to previous findings (e.g., Levis, 2011; Bergström et al., 2006). Furthermore, the finding raises a question regarding the theory of Bergström et al. (2006) on reduced costly information gathering for PE backed IPOs. It could be that investors do not trust PE involvement in FinTech IPOs as much as with non-FinTech IPOs.

Another interesting observation is that proceeds seem to have a positive effect on underpricing in the model, which indicates that larger offerings experience greater underpricing. Contradictory to previous research (e.g., Beatty & Ritter, 1986; Clarkson & Merkley, 1994), the coefficient suggests a statistically significant negative relationship between proceeds and underpricing (p = .0013).

The number of underwriters involved in the issue has a statistically significant negative effect in the model (p = .0411). This corresponds with previously presented theory and empirical evidence by Corwin and Schultz (2005), which states that as syndicate size increases, so does the accuracy of the offer price compared to actual market value. Because larger syndicates result in a higher number of valuations, and a more diverse syndicate composition, it should be more representable of the market.

The standard deviation coefficient estimated in the model, representing a market-based risk of the issue, affects underpricing positively. However, it is not significant at an acceptable level (p = .2104) Nevertheless, the coefficient estimate is in line with the argument that riskier issues should be compensated with a higher level of underpricing (Ritter, 1984; Beatty & Ritter, 1986).

Table 7. 2 Underpricing regression results

Coefficients	Estimate
Intercept	-0.2845 (0.1474)
Proceeds (LN)	0.0898*** (0.0013)
NumberOfUnderwriters	-0.0221** (0.0411)
HAP Dummy	-0.0807* (0.0685)
VCDummy	0.3152*** (0.0000)
PEDummy	0.1216* (0.0978)
Stdev49days	0.0156 (0.2104)
UnderwriterReputation	-0.0088 (0.6333)
Adjusted R-squared	0.336
Observations	70
Degrees of freedom	62
Root mean squared error	0.176
F-statistic	5.98

* Significant at 10%
** Significant at 5%
*** Significant at 1%

7.2 Long-run performance results

7.2.1 Distribution of long-run performance measures

The distribution of the 36-month BHAR results is moderately positively skewed, reporting a skewness of 0.92 and kurtosis of 0.38. However, for the CAR results, we report a skewness of -2.67, which is extremely negative, and an unusually high kurtosis of 12.00. These results are caused by an extreme outlier in the dataset, namely Liquid Holdings LLC. This issue is not delisted in our dataset, despite being out of business. When looking at the stock price quote for this particular issue, it has a 0% return after month 29. As a consequence, this results in an extremely negative abnormal return, because the benchmark index maintains a high return in the comparable period. Because the outlier in the CAR distribution is too high to ignore, we decided to remove it from our sample. By doing so, we achieved a skewness of -0.43 and kurtosis of -0.02, as can be seen in Figure 7.5. The new sample is closer to a normal distribution than the unadjusted data.

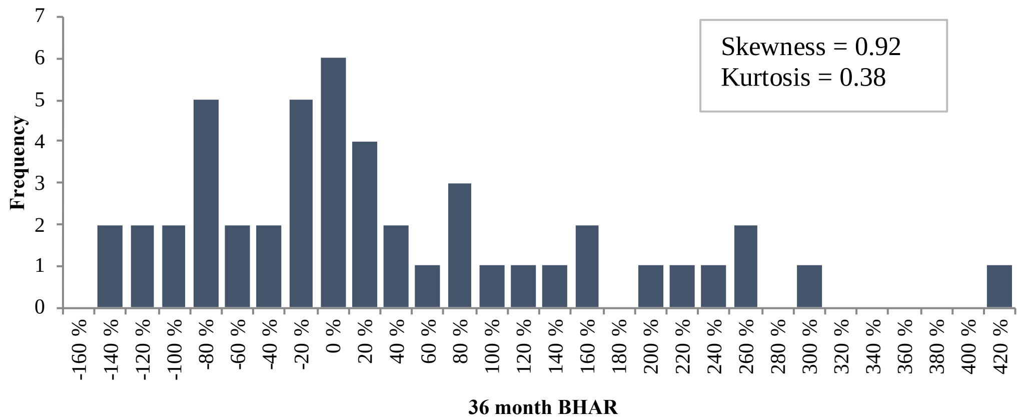

Figure 7. 4 Distribution of 36 month BHAR

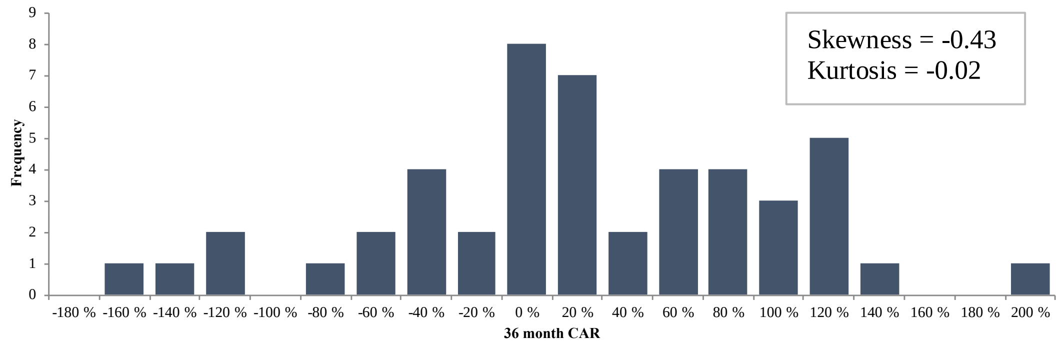

Figure 7. 5 Distribution of 36 month CAR

A Jarque Bera normality test on the 36 months BHARs and CARs shows that the BHARs are significantly non-normal at a 5% significance level (p = .0195), while the CARs are not significantly non-normal at an acceptable level (p > .5000). Thus, we can reject the null hypothesis of the BHARs having a normal distribution, but not for CARs. These results are in line with Fama's (1998) argument that the BHAR metric is skewed because of its compounding nature, while CAR distributions will be closer to normal.

7.2.2 Time series of long-run performance measures

Figure 7.6 shows the abnormal return development of both the CAR and BHAR measure with the seasoning month on the horizontal axis, spanning from the first closing price of the issue until the 36th month of return. As can be seen from this graph, the BHARs show more extreme result than the CARs due to the compounding effect of the BHAR measure. We notice that, up to year 1, the CAR performance metric performs better than the benchmark index. Furthermore, the BHAR performance metric, on the contrary, underperforms in the corresponding period. In a longer time span, this performance relationship is flipped, and the BHARs outperforms the CARs until the end of the measured period. Again, since BHARs are compounded, this is a natural difference between the two return measures.

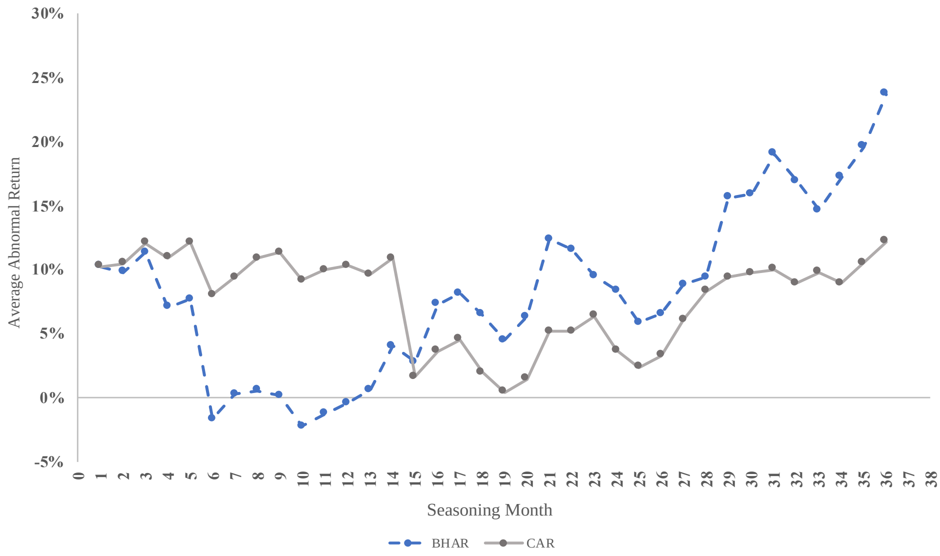

Figure 7. 6 Time series of BHAR and CAR.

7.2.3 Statistical test of abnormal returns

In Table 7.3 and 7.4 the results on the long-run performance is tabulated with corresponding t-statistics from mean difference of zero tests along with skewness and kurtosis for each month. As seen from the tables, none of the abnormal return periods are statistically significantly different than zero. Out of the 36 seasoning months, a positive BHAR is reported in 32 of the 36 months, whereas a positive CAR is reported in all 36 months. However, the results are not statistically significant at an acceptable level, which could be explained by the volatility of the returns and low observation count. Thus, we are not able to find support for Hypothesis 6, stating that FinTech IPOs experience significant underperformance in the long-run. However, disregarding that the results are not statistically significant at an acceptable level, the findings contradicts previous research on IPO performance (e.g., Ritter, 1991; Loughran & Ritter, 1995).

Table 7. 3 Average CAR for each seasoning month

Average CAR per seasoning month for FinTech stocks in the sample with standard deviation, test-statistic from mean-difference t-test, skewness and kurtosis. In the cases where a firm is delisted or merged, it is removed from the CAR measurement. This results in a deminishing number of observations as more months are included.

		CAR					
Month	Observations	Average	Stdev	T-stat	Median	Skewness	Kurtosis
1	69	10.3 %	85.4 %	1.00	1.1 %	8.11	66.77
2	69	10.5 %	86.5 %	1.01	0.2 %	7.54	60.40
3	68	12.1 %	86.8 %	1.16	2.3 %	7.49	59.91
4	68	11.0 %	84.9 %	1.06	-1.1 %	7.21	56.52
5	68	12.2 %	85.5 %	1.17	2.2 %	6.83	52.74
6	68	8.0 %	77.2 %	0.86	7.2 %	6.03	44.94
7	65	9.4 %	92.2 %	0.84	1.5 %	6.42	48.68
8	63	10.9 %	91.8 %	0.96	8.3 %	6.01	44.16
9	60	11.4 %	90.3 %	1.00	6.4 %	5.76	41.27
10	60	9.2 %	87.2 %	0.82	2.5 %	4.94	33.72
11	60	10.0 %	86.3 %	0.90	4.9 %	4.70	31.50
12	59	10.3 %	84.5 %	0.95	8.6 %	4.57	30.53
13	59	9.6 %	81.3 %	0.91	10.5 %	3.73	23.94
14	56	10.9 %	81.8 %	1.03	14.2 %	3.65	23.07
15	56	1.7 %	51.2 %	0.24	10.3 %	-0.89	1.41
16	56	3.7 %	55.9 %	0.49	14.3 %	-0.85	1.67
17	56	4.6 %	54.1 %	0.64	9.2 %	-0.24	0.74
18	55	2.0 %	57.2 %	0.26	13.7 %	-0.46	1.05
19	55	0.4 %	58.5 %	0.06	11.7 %	-0.38	0.65
20	55	1.5 %	60.5 %	0.18	10.1 %	-0.42	0.67
21	55	5.2 %	61.8 %	0.62	10.5 %	-0.21	0.09
22	54	5.2 %	61.1 %	0.63	18.1 %	-0.26	-0.28
23	52	6.4 %	62.6 %	0.75	17.8 %	-0.54	0.23
24	52	3.7 %	63.0 %	0.42	6.6 %	-0.38	-0.25
25	52	2.4 %	64.3 %	0.27	6.5 %	-0.31	-0.02
26	52	3.3 %	66.9 %	0.36	7.7 %	-0.47	-0.34
27	52	6.1 %	66.7 %	0.66	7.7 %	-0.38	-0.33
28	50	8.3 %	67.6 %	0.89	11.7 %	-0.51	-0.03
29	50	9.4 %	70.4 %	0.95	9.6 %	-0.31	-0.01
30	50	9.8 %	72.0 %	0.96	11.1 %	-0.49	0.26
31	50	10.0 %	73.2 %	0.97	9.4 %	-0.30	-0.08
32	50	9.0 %	74.2 %	0.86	16.6 %	-0.43	-0.08
33	49	9.8 %	73.3 %	0.95	13.5 %	-0.38	-0.10
34	48	9.0 %	74.7 %	0.84	12.9 %	-0.37	0.11
35	48	10.6 %	75.2 %	0.97	12.0 %	-0.31	0.28
36	48	12.2 %	77.4 %	1.09	11.5 %	-0.34	0.02

Table 7. 4 Average BHAR for each seasoning month

Average BHAR per seasoning month for FinTech stocks in the sample with standard deviation, test-statistic from mean-difference t-test, skewness, kurtosis and a sign test for year 1, 2 and 3. In the cases where a firm is delisted or merged, it is removed from the CAR measurement. This results in a deminishing number of observations as more months are included.

		BHAR						
Month	Observations	Average	Stdev	T-stat	Median	Skewness	Kurtosis	Sign test
1	69	10.3 %	85.4 %	1.00	1.1 %	8.11	66.77	-
2	69	9.8 %	77.3 %	1.06	-0.2 %	7.30	57.68	-
3	68	11.3 %	85.1 %	1.11	1.0 %	7.42	59.08	-
4	68	7.1 %	57.0 %	1.02	-2.8 %	5.84	41.90	-
5	68	7.7 %	58.0 %	1.10	1.4 %	5.28	36.73	-
6	68	-1.6 %	31.9 %	-0.42	-3.8 %	0.15	-0.21	-
7	65	0.3 %	34.3 %	0.08	-0.8 %	0.45	0.29	-
8	63	0.6 %	36.2 %	0.13	0.0 %	0.19	0.02	-
9	60	0.2 %	40.4 %	0.03	0.0 %	0.58	0.47	-
10	60	-2.2 %	43.4 %	-0.39	-5.5 %	0.31	0.04	-
11	60	-1.2 %	46.0 %	-0.21	-5.5 %	0.30	0.01	-
12	59	-0.4 %	46.1 %	-0.07	-0.2 %	0.18	-0.38	1.00
13	59	0.6 %	50.2 %	0.09	-0.1 %	0.22	-0.44	-
14	56	4.1 %	52.4 %	0.60	0.0 %	0.65	0.48	-
15	56	2.8 %	55.5 %	0.37	-3.9 %	0.79	0.76	-
16	56	7.3 %	64.1 %	0.85	2.2 %	1.15	2.19	-
17	56	8.2 %	73.5 %	0.83	-7.9 %	1.70	4.34	-
18	55	6.5 %	74.0 %	0.66	-2.3 %	1.74	4.68	-
19	55	4.5 %	75.7 %	0.44	0.6 %	1.71	4.48	-
20	55	6.3 %	80.2 %	0.59	-3.4 %	1.75	5.00	-
21	55	12.4 %	88.9 %	1.03	6.1 %	1.81	5.31	-
22	54	11.6 %	83.0 %	1.04	0.0 %	1.35	3.17	-
23	52	9.5 %	83.1 %	0.84	0.0 %	1.59	4.59	-
24	52	8.4 %	80.1 %	0.75	-5.9 %	0.77	0.13	0.89
25	52	5.9 %	82.7 %	0.51	-6.1 %	0.93	0.59	-
26	52	6.6 %	83.9 %	0.57	-3.1 %	0.66	-0.02	-
27	52	8.9 %	87.4 %	0.73	-5.4 %	0.72	-0.10	-
28	50	9.4 %	89.0 %	0.76	-0.8 %	0.79	0.05	-
29	50	15.6 %	102.2 %	1.08	-2.6 %	1.00	0.70	-
30	50	15.9 %	101.1 %	1.12	-6.1 %	0.86	0.25	-
31	50	19.1 %	111.4 %	1.21	-5.6 %	1.11	1.02	-
32	50	17.0 %	109.1 %	1.10	3.4 %	1.02	1.06	-
33	49	14.6 %	110.0 %	0.94	-0.9 %	1.09	1.25	-
34	48	17.2 %	117.6 %	1.03	-3.0 %	1.16	1.34	-
35	48	19.6 %	127.0 %	1.07	-7.2 %	1.61	4.20	-
36	48	23.7 %	127.2 %	1.29	-7.6 %	1.03	0.78	0.67

7.2.4 Multivariate regression analysis

Table 7.5 reports the estimated coefficients for the long-run regression models. In both models, the adjusted R-squared is lower than in the underpricing model. The 3-year CAR model does not explain much of the variation in the long-run performance of FinTech IPOs (ΔR^2 = .134), and the model is only statistically significant at a 10% level (F = 1.91, p = .086). The 3-year BHAR model yields slightly different results, and is not statistically significant at an acceptable level (ΔR^2 = .119, F = 1.79, p = .108). This could partly be explained by the fact that the BHARs cannot be assumed to be normally distributed, which has to be taken into consideration when assessing the results of the coefficient estimates in this model.

The only statistically significant coefficient at a 5% level is the high IPO activity period predictor in the 3-year CAR model (p = .0469). The predictor has a negative effect on long-run performance in this model. Moreover, the 3-year BHAR model also predicts that offerings occurring during a high activity period affect the model negatively, with a relatively low p-value (p = .0553). These results support Hypothesis 8, stating that high IPO activity has a significant negative effect on the long-run performance of FinTech IPOs. Moreover, the result is in line with previous findings by Ritter (1991) and Schultz (2003), and suggest that returns of FinTech IPOs are particularly poor following periods of heavy issuance. Moreover, this finding supports the *pseudo-market timing hypothesis* by Schultz (2003), suggesting that returns should be particularly poor following periods of heavy issuance as a result of higher stock prices in these periods.

The number of unique underwriters involved in the deal seems to have a negative effect in the 3-year BHAR model. However, the coefficient is only statistically significant at a 10% significance level (p = .070). In the 3-year CAR model, the coefficient also indicates a negative relationship between number of underwriters and long-run performance of FinTech IPOs. Nonetheless, the coefficient is not statistically significant at an acceptable level (p = .109). These results contradicts previous empirical findings by Dong et al. (2011), which suggests that a syndicate with a higher number of unique underwriters should perform better in the long-run. Considering these results, and the fact that the coefficient yields a relatively low statistical significance in both models, we find no support for Hypothesis 7.

It is also worth mentioning the standard deviation coefficient from the first 49 days, which is statistically significant at a 10% significance level in the 3-year CAR model (p = .062). The coefficient predicts a negative impact on the long-run performance in this model, which indicates that issues with a more “rocky start” during the first 49 days after the IPO date is expected to perform worse in the long-run compared to the more stable issues. However, the coefficient is not statistically significant at an acceptable level in the 3-year BHAR model (p = .199).

Table 7. 5 3-year CAR and BHAR regression results

* Significant at 10%
** Significant at 5%
*** Significant at 1%

Coefficients	**3-Year CAR**	**3-Year BHAR**
Intercept	2.0491	3.4237
	(0.1681)	(0.1561)
Proceeds (LN)	0.0606	0.1813
	(0.6900)	(0.4632)
NumberOfUnderwriters	-0.0865	-0.1595*
	(0.1092)	(0.0700)
HAP Dummy	-0.4661**	-0.7284*
	(0.0469)	(0.0553)
VCDummy	0.5580	0.9685
	(0.2252)	(0.1952)
PEDummy	0.5024	0.7811
	(0.1997)	(0.2188)
Stdev49days	-0.2365*	-0.2608
	(0.0619)	(0.1991)
UnderwriterReputation	-0.6595	-1.6545
	(0.4253)	(0.2203)
FirstDayReturn	-0.1848	-0.3744
	(0.2005)	(0.1121)
Adjusted R-squared	0.134	0.119
Observations	48	48
Degrees of freedom	39	39
Root mean squared error	0.735	1.19
F-statistic	1.91	1.79

8. Conclusion

The main objective of this thesis is to answer the research question *"How does FinTech IPOs in the US perform in the short- and long-run?"*. By examining a dataset consisting of 70 FinTech IPOs issued between 2008 and 2018, the results provide evidence of significant underpricing for FinTech IPOs in this period. The findings also indicate that FinTech IPOs experienced higher first day returns, compared to the overall IPO market in the US. These results provide further evidence of previously reported underpricing of technology companies by Loughran and Ritter (2004) and Karlis (2008). Furthermore, we argue that underpricing can be a compensation for the riskiness of FinTech IPOs, as a result of the uncertainty and early development stage of the sector.

From the multivariate regression analysis on first-day returns, the results show that underwriter reputation does not have a significant effect on underpricing of FinTech IPOs. Moreover, FinTech IPOs listed during the high activity period seem to experience lower degrees of underpricing. This finding is in line with previous results on IPOs underpricing by Ibbotson et al. (1988) and Lowry and Schwert (2002), suggesting that underwriters use the information in the market when valuing the issues. However, the most significant finding from the regression analysis is the highly significant effect VC backing has on first-day returns of FinTech IPOs. This finding in line with previous research by Lee and Wahal (2004). We argue that this could be because VC firms typically invest in young firms with high-growth opportunities.

In the long-run perspective, the results do not provide evidence of underperformance of FinTech IPOs. Contradictory to our prediction, the results indicate that FinTech IPOs perform better in the long-run compared to stocks in similar industries. However, the results are not significant at an acceptable level and could be explained by randomness alone. Nevertheless, the findings contradict previous research on IPO performance by Ritter (1991) and Loughran and Ritter (1995). The results from the multivariate regression analysis on long-run performance indicate that IPOs issued during high IPO activity periods have a negative effect on abnormal returns. This result is in line with previous findings by Ritter (1991) and Schultz (2003), and suggests that returns of FinTech IPOs are particularly poor following periods of heavy issuance.

8.1 Limitations and future research

An obvious limitation to this study is the limited observation count. This challenge will naturally solve itself as more FinTech companies become publicly listed in the future, offering far more reliable results in a replicated study. A way to increase the number of observations could be looking at other regions, such as Europe and Asia, in addition to the US market.

Another recommendation for future research should be to look at the cause of why VC backing leads to such significantly higher levels of underpricing for FinTech IPOs. For example, one could look at the composition of the VC pool and develop categorical data to get to the root of this observation, e.g. by developing a ranking system for the VC companies or the age of the VC company itself.

For future research, it is also recommended to look at the long-run performance of FinTech IPOs in both calendar time and event time. The calendar time approach is perhaps more applicable to a real-life scenario for investors. Comparing the two different measurements might also reveal some timing strategies in the market.

9. References

Akerlof, G. A. (1970). The market for "lemons": Quality Uncertainty and the Market Mechanism. *Quarterly Journal of Economics*, 84(3), 488-500.

Arner, W. D., Barberis, J., & Buckley, R. P. (2016). The evolution of Fintech: A new post-crisis paradigm. *Georgetown Journal of International Law*, 47, 1271.

Barber, B. M., & Lyon, J. D. (1997). Detecting long-run abnormal stock returns: The empirical power and specification of test statistics. *Journal of Financial Economics*, 43(3), 341-372.

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.

Bergström, C., Nilsson, D., & Wahlberg, M. (2006). Underpricing and long-run performance patterns of European private-equity-backed and non-private-equity-backed IPOs. *The Journal of Private Equity, 9*(4), 16.

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.

Carter, R. B., Dark, F. H., & Singh, A. K. (1998). Underwriter reputation, initial returns, and the long-run performance of IPO stocks. *The Journal of Finance*, 53(1), 285-311.

Carter, R., & Manaster, S. (1990). Initial public offerings and underwriter reputation. *The Journal of Finance*, 45(4), 1045-1067.

Clarkson, P. M., & Merkley, J. (1994). Ex ante uncertainty and the underpricing of initial public offerings: Further Canadian evidence. *Canadian Journal of Administrative Sciences*, 11(2), 54-67.

Corwin, S. A., & Schultz, P. (2005). The role of IPO underwriting syndicates: Pricing, information production, and underwriter competition. *The Journal of Finance.*, 60(1), 443-486.

Dong, M., Michel, J. S., & Pandes, J. A. (2011). Underwriter quality and long-run IPO performance. *Financial Management*, 40(1), 219-251.

Fama, E. F. (1998). Market efficiency, long-term returns, and behavioral finance. *Journal of Financial Economics, 49*(3), 283-306.

Financial Technology Partners. (2019). *U.S. Fintech IPO analysis.* Retrieved from Financial Technology Partners: https://ftpartners.docsend.com/view/e2cggu7

Gomber, P., Koch, J. A., & Siering, M. (2017). Digital Finance and FinTech: current research and future research directions. *Journal of Business Economics*, 87(5), 537-580.

Gompers, P. A. (1996). Grandstanding in the venture capital industry. *Journal of Financial Economics*, 42(1), 133-156.

Gompers, P., & Lerner, J. (1998). Venture capital distributions: Short-run and long-run reactions. *The Journal of Finance*, *53*(6), 2161-2183.

Ibbotson, R. G. (1975). Price performance of common stock new issues. *Journal of Financial Economics*, *2*(3), 235-272.

Ibbotson, R. G., & Jaffe, J. F. (1975). “Hot issue” markets. *The Journal of Finance*, 30(4), 1027-1042.

Ibbotson, R. G., Sindelar, J. L., & Ritter, J. R. (1988). Initial public offerings. *Journal of applied corporate finance*, 1(2), 37-45.

Ibbotson, R. G., Sindelar, J. L., & Ritter, J. R. (1994). The market's problems with the pricing of initial public offerings. *Journal of Applied Corporate Finance*, 7(1), 66-74.

Jensen, M. C. (1986). Agency costs of free cash flow, corporate finance, and takeovers. *The American Economic Review, 76*(2), 323-329.

Karlis, P. L. (2008). IPO underpricing. *The Park Place Economist*, 8(1), 81-89.

Krigman, L., Shaw, W. H., & Womack, K. L. (1999). The persistence of IPO mispricing and the predictive power of flipping. *The Journal of Finance*, 54(3), 1015-1044.

Lee, P. M., & Wahal, S. (2004). Grandstanding, certification and the underpricing of venture capital backed IPOs. *Journal of Financial Economics*, 73(2), 375-407.

Lee, S. (2015). Fintech and Korea's financial investment industry. *Capital Market Opinion*.

Levis, M. (2011). The performance of private equity-backed IPOs. *Financial Management*, *40*(1), 253-277.

Ljungqvist, A., & Wilhelm Jr., W. J. (2003). IPO pricing in the dot-com bubble. *The Journal of Finance, 58*(2), 723-752.

Ljungqvist, A., Nanda, V., & Singh, R. (2006). Hot markets, investor sentiment, and IPO pricing. *The Journal of Business*, 79(4), 1667-1702.

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

Loughran, T., & Ritter, J. R. (1995). The new issues puzzle. *The Journal of Finance*, 50(1), 23-51.

Lowry, M., & Schwert, G. W. (2002). IPO market cycles: Bubbles or sequential learning? *The Journal of Finance*, 57(3), 1171-1200.

Michaely, R., & Shaw, W. (1994). The pricing of initial public offerings: Tests of adverse-selection and signaling theories. *The Review of Financial Studies,* 7(2), 279-319.

Nanda, V., & Yun, Y. (1997). Reputation and financial intermediation: An empirical investigation of the impact of IPO mispricing on underwriter market value. *Journal of Financial Intermediation*, 6(1), 39-63.

Ritter, J. R. (1984). The "hot issue" market of 1980. *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), 46(1), 3-27.

Ritter, J. R. (2015). Growth Capital-Backed IPOs. *Financial Review, 50*(4), 481-515.

Ritter, J. R., & Welch, I. (2002). A review of IPO activity, pricing, and allocations. *The Journal of Finance*, 57(4), 1795-1828.

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

Schultz, P. (2003). Pseudo market timing and the long-run underperformance of IPOs. *The Journal of Finance, 58*(2), 483-517.

10. Appendices

Appendix 1: FinTech IPO dataset

Table 10. 1 List of FinTech IPOs with characteristics

Issue Date	Issuer	Underpricing	3YearCAR	3YearBHAR	Number of Underwriters	Lead underwriter	Underwriter reputation rank	Venture Capital Backed	Private Equity Backed
18/03/2008	Visa Inc	28 %	10 %	3 %	8	JP Morgan	9	No	No
30/07/2014	Synchrony Financial	0 %	-6 %	-23 %	8	Goldman Sachs & Co	9	No	No
14/10/2015	First Data Corp	-2 %	23 %	-8 %	13	Citigroup Global Markets In	9	No	Yes
06/10/2009	Verisk Analytics Inc	24 %	16 %	28 %	2	Merill Lynch & Co	9	No	No
22/01/2014	Santander Consumer USA Hldgs	5 %	-67 %	-79 %	13	Citigroup Global Markets In	9	No	Yes
23/05/2018	GreenSky Inc	2 %	N/A	N/A	7	Goldman Sachs & Co	9	No	Yes
10/12/2014	LendingClub Corp	56 %	-140 %	-125 %	4	Goldman Sachs & Co	9	Yes	No
03/11/2011	Groupon Inc	31 %	-136 %	-149 %	11	Morgan Stanley	9	Yes	No
24/06/2015	TransUnion	13 %	68 %	122 %	7	Goldman Sachs & Co	9	No	Yes
11/10/2012	Workday Inc	74 %	3 %	-16 %	4	Morgan Stanley	9	Yes	No
26/04/2018	DocuSign Inc	37 %	N/A	N/A	5	Morgan Stanley	9	Yes	No
11/02/2015	Inovalon Holdings Inc	0 %	-72 %	-96 %	5	Goldman Sachs & Co	9	No	No
25/04/2018	Ceridian Hcm Hldg Inc.	42 %	N/A	N/A	9	Goldman Sachs & Co	9	No	Yes
15/04/2015	Virtu Financial Inc	17 %	12 %	-7 %	8	Goldman Sachs & Co	9	No	Yes
14/12/2010	FleetCor Technologies Inc	18 %	104 %	255 %	4	Goldman Sachs & Co	9	Yes	No
11/10/2018	Anaplan Inc	43 %	N/A	N/A	3	Goldman Sachs & Co	9	Yes	No
24/01/2008	RiskMetrics Group Inc	36 %	-7 %	-26 %	3	Credit Suisse	9	Yes	No
18/11/2015	Square Inc	45 %	182 %	413 %	8	Goldman Sachs & Co	9	Yes	No
26/03/2014	TriNet Group Inc	19 %	18 %	-8 %	3	JP Morgan	9	No	Yes
25/05/2016	Cotiviti Holdings Inc	-10 %	N/A	N/A	10	Goldman Sachs & Co	9	No	Yes
18/04/2013	Blackhawk Network Holdings Inc	13 %	-5 %	-22 %	4	Goldman Sachs & Co	9	No	No
22/05/2018	Evo Payments INC	19 %	N/A	N/A	5	JP Morgan	9	No	Yes
16/03/2017	MuleSoft Inc	46 %	N/A	N/A	6	Goldman Sachs & Co	9	Yes	No
18/10/2010	NetSpend Holdings Inc	18 %	11 %	-35 %	2	Goldman Sachs & Co	9	No	Yes
16/12/2014	On Deck Capital Inc	40 %	-167 %	-132 %	5	Morgan Stanley	9	Yes	No
28/02/2017	Hamilton Lane Inc	13 %	N/A	N/A	2	JP Morgan	9	No	No
14/06/2018	Avalara Inc	87 %	N/A	N/A	3	Goldman Sachs & Co	9	Yes	No
21/07/2010	Green Dot Corp	22 %	-85 %	-115 %	2	JP Morgan	9	Yes	No
11/04/2018	Zuora Inc	43 %	N/A	N/A	4	Goldman Sachs & Co	9	Yes	No
14/04/2016	BATS Global Markets Inc	21 %	N/A	N/A	7	Morgan Stanley	9	No	Yes
27/10/2016	Blackline Inc	39 %	N/A	N/A	2	Goldman Sachs & Co	9	No	No
05/08/2010	IntraLinks Holdings Inc	0 %	-37 %	-99 %	3	Morgan Stanley	9	No	Yes
27/07/2017	Redfin Corp	45 %	N/A	N/A	4	Goldman Sachs & Co	9	Yes	No
05/10/2016	Coupa Software Inc	85 %	N/A	N/A	4	Morgan Stanley	9	Yes	No
30/07/2014	HealthEquity Inc	26 %	101 %	146 %	2	JP Morgan	9	No	Yes
15/03/2010	Financial Engines Inc	44 %	48 %	55 %	1	Goldman Sachs & Co	9	Yes	No
05/03/2014	TriplePoint Venture Growth BDC	4 %	-42 %	-50 %	5	Morgan Stanley	9	No	No
18/03/2014	Paylocity Holding Corp	41 %	41 %	9 %	3	Deutsche Bank	8	Yes	No
24/03/2011	ServiceSource International	22 %	-37 %	-97 %	2	Morgan Stanley	9	Yes	No
24/01/2012	Guidewire Software Inc	32 %	77 %	118 %	3	JP Morgan	9	Yes	No
16/06/2010	Higher One Holdings Inc	19 %	-57 %	-83 %	1	Goldman Sachs & Co	9	No	Yes
29/10/2014	Fifth St Asset Mgmt Inc	-21 %	-58 %	-116 %	9	Morgan Stanley	9	No	No
19/09/2012	Trulia Inc	41 %	58 %	37 %	2	JP Morgan	9	Yes	No
14/02/2013	Xoom Corp	59 %	-13 %	-53 %	2	Barclays	9	Yes	No
19/03/2014	Q2 Holdings Inc	17 %	61 %	74 %	2	JP Morgan	9	Yes	No
11/12/2014	Workiva Inc	-2 %	25 %	15 %	2	Morgan Stanley	9	Yes	No
18/06/2015	MINDBODY Inc	-17 %	96 %	184 %	3	Morgan Stanley	9	No	Yes
14/04/2014	Paycom Software Inc	2 %	118 %	215 %	2	Barclays	9	No	Yes
20/03/2014	Amber Road Inc	31 %	-57 %	-86 %	1	Stifel Nicolaus & Co Inc	9	Yes	No
06/12/2017	Curo Grp Holdings Corp	1 %	N/A	N/A	3	Credit Suisse	9	No	Yes
24/06/2009	Medidata Solutions Inc	21 %	13 %	2 %	2	Citigroup Global Markets In	9	Yes	No
14/03/2012	Demandware Inc	47 %	67 %	79 %	2	Goldman Sachs & Co	9	Yes	No
20/06/2018	I3 Verticals Inc	41 %	N/A	N/A	3	Cowen & Co	8	Yes	No
27/06/2018	Everquote Inc	0 %	N/A	N/A	2	JP Morgan	9	Yes	No
14/12/2010	GAIN Capital Holdings Inc	-2 %	-4 %	-38 %	2	Morgan Stanley	9	Yes	No
09/08/2012	Performant Financial Corp	18 %	-157 %	-143 %	4	Morgan Stanley	9	No	Yes
05/04/2017	Elevate Credit Inc	19 %	N/A	N/A	3	UBS Securities Inc	7	Yes	No
20/03/2014	Borderfree Inc	25 %	-6 %	-70 %	2	Credit Suisse	9	Yes	No
02/10/2014	Yodlee Inc	12 %	0 %	-16 %	4	Goldman Sachs & Co	9	Yes	No
25/06/2015	AppFolio Inc	17 %	109 %	235 %	2	Morgan Stanley	9	Yes	No
09/02/2018	Cardlytics Inc	3 %	N/A	N/A	2	Merill Lynch & Co	9	Yes	No
03/04/2014	Five9 Inc	9 %	82 %	67 %	3	JP Morgan	9	Yes	No
28/07/2010	Envestnet Inc	14 %	57 %	81 %	3	Morgan Stanley	9	Yes	No
08/02/2012	FX Alliance Inc	15 %	0 %	-7 %	4	Bank of America	9	Yes	No
09/05/2012	WageWorks Inc	40 %	114 %	245 %	2	William Blair & Co	7	Yes	No
05/12/2017	Credible Labs Inc	43 %	N/A	N/A	1	Bell Potter Securities Ltd	1	Yes	No
08/12/2017	Longfin Corp	8 %	N/A	N/A	1	Network 1 Financial Securit	6	No	No
22/04/2010	SPS Commerce Inc	13 %	94 %	156 %	1	Thomas Weisel Partners	4	Yes	No
14/04/2011	Ellie Mae Inc	13 %	132 %	296 %	1	Barclays	9	Yes	No
25/07/2013	Liquid Holdings Group Inc	-15 %	#N/A	#N/A	1	Sandler O'Neill Partners L.I	9	No	No

Appendix 2: Yearly distribution of IPOs in 2008-2018

All IPOs are included in table 10.4, whereas penny stocks are excluded in table 10.3

Table 10. 2 Distribution of initial public offerings (including penny stocks)

	Number of IPOs		Proceeds ($ millions)		Underpricing	
Year	*All IPOs*	*Fintech IPOs*	*All IPOs*	*Fintech IPOs*	*All IPOs*	*Fintech IPOs*
2008	31	2	25 472	18 109	3.1 %	32.1 %
2009	28	2	17 328	1 964	15.6 %	22.6 %
2010	61	9	39 959	1 231	6.2 %	16.3 %
2011	38	3	36 711	864	12.7 %	21.7 %
2012	104	7	49 190	1 144	10.0 %	38.1 %
2013	222	3	62 182	360	11.8 %	19.1 %
2014	207	16	51 356	7 081	11.4 %	16.5 %
2015	132	7	25 215	4 556	11.6 %	10.5 %
2016	66	4	12 056	664	11.5 %	33.9 %
2017	134	7	28 240	824	9.2 %	25.0 %
2018	116	10	30 947	3 028	10.8 %	31.6 %
Total	**1139**	**70**	**378 654**	**39 826**	**10.7 %**	**23.0 %**
Yearly Average	104	6	34 423	3 621	10.3 %	24.3 %
Yearly Median	104	7	30 947	1 231	11.4 %	22.6 %

Table 10. 3 Distribution of initial public offerings (excluding penny stocks)

	Number of IPOs		Proceeds ($ millions)		Underpricing	
Year	*All IPOs*	*Fintech IPOs*	*All IPOs*	*Fintech IPOs*	*All IPOs*	*Fintech IPOs*
2008	28	2	25 414	18 109	3.8 %	32.1 %
2009	28	2	17 328	1 964	15.6 %	22.6 %
2010	56	9	39 572	1 231	4.0 %	16.3 %
2011	32	3	36 361	864	9.8 %	21.7 %
2012	89	7	48 890	1 144	11.0 %	38.1 %
2013	209	3	61 892	360	11.2 %	19.1 %
2014	194	16	51 209	7 081	11.4 %	16.5 %
2015	120	7	24 675	4 556	11.6 %	10.5 %
2016	62	4	11 942	664	11.0 %	33.9 %
2017	123	5	27 948	723	10.6 %	21.9 %
2018	107	10	30 769	3 028	10.6 %	31.6 %
Total	**1048**	**68**	**375 998**	**39 725**	**10.6 %**	**22.7 %**
Yearly Average	95	6	34 182	3 611	10.0 %	24.0 %
Yearly Median	89	5	30 769	1 231	11.0 %	21.9 %

Appendix 3: Underwriter reputation ranking

Table 10. 4 Underwriter reputation scores

Underwriter	Times as lead	Times represented	Proceeds handled as lead ($ m)	Total proceeds handled ($ m)	Ritter score	Times as lead score	Times represented score	Proceeds handled as lead ($ m) score	Total proceeds handled ($ m) score	Total Reputation score
JP Morgan	124	410	28 828	178 564	9	9	9	9	9	9.0
Goldman Sachs & Co	172	355	56 554	181 394	9	9	9	9	9	9.0
Citigroup Global Markets	94	510	27 493	250 582	9	9	9	9	9	9.0
Merill Lynch & Co	73	409	20 930	195 746	8.5	9	9	9	9	9.0
Morgan Stanley	183	404	89 033	203 143	9	9	9	9	9	9.0
Credit Suisse	80	268	15 886	126 711	8.5	9	9	9	9	9.0
Deutsche Bank	18	92	2 355	58 814	8.5	8	9	8	9	9.0
Barclays	47	182	13 043	104 400	8	9	9	9	9	9.0
Stifel Nicolaus & Co Inc	27	79	2 542	8 152	7	9	8	8	8	8.0
Cowen & Co	13	76	965	7 885	7	8	8	8	8	8.0
UBS Securities Inc	9	51	7 900	25 284	8.5	7	8	9	8	8.0
Bank of America	68	215	22 629	123 421	8.5	9	9	9	9	9.0
William Blair & Co	7	37	362	4 278	7	7	8	7	7	7.0
Bell Potter Securities Ltd	1	1	51	51	N/A	1	1	4	3	2.0
Network 1 Financial Secur	4	5	77	82	3	6	5	5	4	5.0
Thomas Weisel Partners	2	2	95	95	7	4	3	5	4	5.0
Sandler O'Neill Partners L	29	40	2 123	3 966	N/A	9	8	8	7	8.0

Appendix 4: Correlation matrix of coefficients

The correlation matrix in table 10.5 shows the correlation between coefficients in the underpricing and long-run performance regressions.

Table 10. 5 Correlation matrix of coefficients

	LN(Proceeds)	NumberOfUnderwriters	HAP	VCDummy	PEDummy	STD49Days	FirstDayReturn	UnderwriterReputation
LN(Proceeds)	1.000	0.666	-0.028	-0.354	0.192	0.038	0.070	0.266
NumberOfUnderwriters	0.666	1.000	-0.081	-0.355	0.358	-0.052	-0.143	0.230
HAP	-0.028	-0.081	1.000	0.087	0.065	0.008	-0.100	0.095
VCDummy	-0.354	-0.355	0.087	1.000	-0.700	0.103	0.506	-0.148
PEDummy	0.192	0.358	0.065	-0.700	1.000	-0.167	-0.331	0.154
STD49Days	0.038	-0.052	0.008	0.103	-0.167	1.000	0.232	-0.062
FirstDayReturn	0.070	-0.143	-0.100	0.506	-0.331	0.232	1.000	-0.072
UnderwriterReputation	0.266	0.230	0.095	-0.148	0.154	-0.062	-0.072	1.000