US Fintech Sector: Short-run and Long-run Performance of Initial Public Offerings

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ABSTRACT

The present master thesis develops an analysis of the short-run and long-run performance of initial public offerings (IPOs) in the US fintech industry between 2005 and 2018. A sample of 128 fintech companies is analysed in the following study. As regards to the short-run performance, a mean initial return of 19.35% is observed. Moreover, the existence of ex-ante and ex-post proxies for uncertainty is rejected, which is strongly in contrast with previous literature on this subject. Concerning the long-run performance, two approaches are followed: the event-time and the calendar-time approaches. After applying these two methods, it is shown that underperformance is not a phenomenon witnessed in the US fintech sector. In fact, although with a few exceptions, the results are more inclined to the existence of positive abnormal returns. Nevertheless, findings are not as clear as for the short-run case.

Keywords: Fintech, Initial Public Offerings, Underpricing, Long-run performance

SUMÁRIO

A presente tese de mestrado desenvolve uma análise do desempenho a curto e longo prazo de ofertas públicas iniciais (IPOs) da indústria *fintech* dos EUA entre 2005 e 2018. Uma amostra de 128 empresas de fintech foi utilizada neste estudo. Para o desempenho a curto prazo, observa-se um retorno inicial médio de 19,35%. Além disso, a existência de proxies para a incerteza ex-ante e ex-post é rejeitada, o que contrasta fortemente com a literatura anterior sobre esta matéria. Relativamente ao desempenho a longo prazo, são efectuadas duas abordagens: *event-time* e *calendar-time*. Depois de aplicar estes dois métodos, é possível mostrar que *underperformance* não é um fenômeno observado no sector *fintech* dos EUA. De facto, embora com algumas excepções, os resultados são mais propensos à existência de retornos anormais positivos. No entanto, as descobertas não são de análoga clareza quanto ao acontecimento a curto prazo.

Preface and Acknowledgements

During my five years as a student in Católica Lisbon, innumerous experiences and challenges determined the man that I am today. This thesis is the culmination of all knowledge and competences that I have acquired during my academic course, as well as the last step that I am conducting before initiating my professional career.

I would like first to turn to God with a gesture of gratitude for the life that He had granted me. Subsequently, accomplishing this thesis would not be feasible without the presence of Professor João Freire de Andrade, who contributed substantially with objective comments, precise observations, and know-how, but also with motivation and expertise.

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1. Introduction

On the 19th of November, 2015, Square Inc went public on the New York Stock Exchange (NYSE), and its shares realized a return around 45% from the IPO price. The New York Times wrote after this event:

> *"The early gain in Square's shares bodes well for investors that acquired I.P.O. shares in the San Francisco-based start-up. It is also a better signal for the tech I.P.O. market as a whole"*

Square Inc is not exclusively a tech company, but also a famous fintech, which basically allows sellers with a mobile device to accept card payments from customers. Nonetheless, this is not the only case in recent years of known fintech companies that attained high returns in the first trading day. LendingClub, an online lending platform that matches borrowers and investors with better conditions than traditional banks, and OnDeck Capital, which underwrites and supplies loans to small businesses, by assessing customers based on, among other factors, on online sentiment, gained around 51% and 40%, respectively.

"Fintech", which is an abbreviation of financial technology, is probably one of the most popular buzzwords in the financial world nowadays. In a broad sense, it refers to every type of technology that enables solutions in the financial side of the economy (Arener, Barberis and Buckley, 2015). This term is not confined to particular industries (e.g., financial industry), or to specific business models (for instance, peer-to-peer (P2P) lending), rather it includes the whole extension of financial products and services that traditionally were supplied by the financial industry.

Even though the Automated Teller Machine (ATM) was being introduced by the Barclays Bank in 1967 and, consequently, the modern period for financial technology began, it was only after the 2008 global financial crisis that a new era for fintech companies emerged. At this moment, brand-new start-ups and consolidated tech corporations have started providing financial services and products directly to the public. Not few people believe that the financial world is on the edge of a revolution.

> “*the need for technology is increasing at a breathless pace, for if you ask about the state of our industry today, the answer is that we are in the midst of a revolution.”*
> *– Adena Friedman, President, and CEO, Nasdaq*

Since 2005, the amount raised in fintech IPOs for the US market is around $59 billion with $20 billion just in 2014 (Financial Technology Partners, 2018). The amount raised by fintech US companies in the year of 2017 represented, approximately, 5% of the total amount of proceeds raised in that year for Nasdaq and NYSE together (EY, 2017). Additionally, in the last quarter of 2017, global fintech investments reached $8.7 billion along 307 deals (KPMG, 2017).

Bearing all this in mind, the aim of this work is to study the performance of fintech IPOs, restricting the range of companies to the US market. Commonly in the literature, this sort of analysis is not conducted focusing exclusively on one particular sector. However, there are related papers studying the performance of tech companies, as the case of Beck (2017), which refers to the underpricing in this sector, or Guo, Lev, and Zhou (2005), that analysed the performance of biotech companies.

As regards to the IPO fintech industry, research concerning this field is practically nonexistent or very primitive. It follows that the purpose is to give and enlarge insights into the behaviour of these stocks both in the short and in the long-run. Summarizing, the master research question could be arranged in the following manner: how do US fintech stocks behave both in the short and in the long-run after their IPO?

For the short-run, an underpricing level of 19.35% is identified for the entire sample, and there is no evidence of ex-ante or ex-post proxies being significantly estimators of the IPO initial returns. Concerning the long-run analysis, the behaviour of the US fintech industry does not show evidence of underperformance. In fact, a considerable number of methods is indicating that during the time range being considered positive abnormal returns are attained.

The structure of this thesis is as follows: Chapter 2 summarizes the relevant literature. The collected data is thoroughly explained in Chapter 3, while Chapter 4 describes the methodology used. The results are then analysed in Chapter 5. Chapter 6 refers to limitations and future studies that might be conducted. Chapter 7 contains the major conclusions. In Chapter 8, all references are mentioned, and finally, Chapter 9 includes all appendices.

2. Literature review on IPOs

An IPO occurs when a company´s equity is available to the public for the first time, i.e., when a privately held company goes public. There are three anomalies frequently discussed in the literature that this master thesis will review. After clarifying these phenomena, it is relevant for further analysis to elaborate a number of hypotheses.

2.1. Underpricing

The underpricing anomaly is a phenomenon which takes place consistently in empirical studies of initial equity offerings worldwide. It is defined as the positive percentage difference between the closing price on the first trading day and the offer price.

In past decades, scholars have been trying to understand the causes behind the issue called the "underpricing puzzle". Ibbotson (1975) was one of the first that discovered this peculiar phenomenon: he obtained that the average US initial return during the 1960s was around 11.4%. Moreover, Ritter (1984) observed an average level of initial return level of 18.8 % for 5000 US companies, between the years of 1960 and 1982. More recently, Ritter (2017) observed a positive 14% initial return from 2001 until 2016.[1]

The first fact that should be mentioned is that underpricing is a cost to the issuer. Firms that had an underpricing experience are described as "leaving money on the table". In other words, only part of the intrinsic value of the firm is issued in the stock exchange. The other part of additional proceeds that could have been generated is the opportunity cost of launching an IPO. This is a sort of a paradox: firms in the presence of a perfect and efficient capital market should not be comfortable when "leaving money on the table". Yet, it seems like they want always to assume this cost.

Almost all theoretical explanations are derived from the hypothesis of asymmetrical information among agents, which is also the theory that this thesis is trying to develop even further. Afterwards, the most important theories of underpricing for the present dissertation are summarized.

[1] Additional, Ritter (2017) detected an average initial return of 16.8% during 1960-2018 for 13.001 US firms.

2.1.1. Asymmetric information between the issuing firm and the underwriter

One of the first economists that constructed a model to answer the underpricing puzzle was Baron (1982). It relies on the assumption that the investment banker (IB) knows more about the market´s demand than the issuer. In exchange for sharing the use of information, the underwriter must be paid. The price, and consequently the cost for the issuer, is the level of underpricing.

Underpricing is the cost of the work of the underwriter. The IB takes advantage of their superior knowledge of market clearing conditions and tries to reduce its distribution efforts by reducing the proceeds. Although this argument may contain some true meaning, particularly if issuers are not very sophisticated, it was refuted by Muscarella and Vetsuypens (1989) when they observed that investment banks going public tend to underprice their own shares by as much as other IPOs of similar amount of proceeds (e.g., Morgan Stanley being the underwriter of Morgan Stanley´s initial public offering).

2.1.2. The winner's curse

One of the most important and significant models that try to deal with this asymmetric information issue is the model proposed by Rock (1986), which is derived from Arkelof´s (1970) lemons problem. Rock relies on the hypothesis that there are two types of investors: completely informed and completely uninformed, about the valuation of a given company after the offering price is set. In this way, completely informed investors are able to avoid participating in overvalued IPOs. These informed investors bid only for underpriced IPOs, while uninformed agents always engage in the bidding.

This is a famous adverse selection problem known as the "winner's curse". In overvalued equity offerings, all shares will be allocated completely to uninformed agents, whereas in an undervalued IPO this kind of investors will be allocated to a rationed demand. This happens because informed investors participate when the IPO is undervalued and will crowd uninformed agents out partially (or even entirely).

Rock establishes the assumption that the primary market is only able to cover all the demand of a given IPO if uninformed investors take part. This way, the issuer must give them an incentive to participate always in the bidding. Hence, this incentive will be an offer price that will be regularly lower than the expected value of the stock.[2] As a result, underpricing incorporates into the game less informed investors and solves the winner´s curse problem. In recent literature, such as in Berk and DeMarzo (2014), this explanation is still adopted.

Following Ritter (1984) and, afterwards, Beatty and Ritter (1986), empirical evidence is used to support that underpricing should be related to the "ex-ante uncertainty". Beatty and Ritter derived an application of Rock´s model (1986) to show how the level of underpricing and the level of ex-ante uncertainty are related to the value of the company. They concluded there was a robust relationship: the higher the ex-ante uncertainty is, the higher the level of underpricing will be. In the context of this thesis, tests on the "ex-ante uncertainty" for fintech companies are performed.

2.1.3. Signalling Hypothesis

In contrast to the ex-ante uncertainty hypothesis, the signalling hypothesis proposes that companies send signals to investors by selling their IPOs at discount, thereby showing that high-quality IPO issuers would underprice more to indicate their quality.

Signalling models focus on the argument proposed by Ibbotson (1975), by justifying underpricing as a way to "leave a good taste" in investor´s mouths. This allows companies to sell future equity at a higher price than in the opposite scenario. Underpricing is considered by the external investors as a positive signal concerning the quality of the company, since, in the end, only "good" firms are able to recover from leaving money on the table. Allen and Faulhaber (1989) advocate this theory.

Welch (1989) is of the same spirit of Allen and Faulhaber (1989). Nevertheless, Welch assumes that there are direct costs that "bad" companies face to be able to imitate "good" companies. These costs are aggravated if "good" companies increase the level of underpricing.

Lastly, Grinblatt and Hwang (1989) explore the relationship between underpricing and project risk. The riskier a given firm is, the higher would be its level of underpricing. This is

[2] Rock declares that: *"The analysis shows that the equilibrium offer price includes a finite discount to attract uninformed investors".*

very similar to the result under the winner´s curse, where it was suggested that ex-ante uncertainty and underpricing had a positive relationship.

2.2. Long-term underperformance

The second anomaly to be analysed is the long-term underperformance of IPOs. Underperformance refers to the poor performance of returns of IPOs on average in the long-run spectrum. Several factors make the long-term performance of IPOs a phenomenon of interest. First, it is important for investors, because if the market presents price trends, it may be possible to create opportunities in active trading, and gain positive abnormal returns (Ritter, 1991). Moreover, if the after-market performance shows some sort of pattern, this leads to conclude that there is no efficiency in the information of the initial public offering market. And this will converge to the argument of Shiller (1990), which states that the equity capital markets suffer from fads[3] that affect the market equilibrium.

An underperformance of 51% over a five-year period between 1970 and 1990 in the US is observed in Loughran and Ritter (1995). They argue that firms tend to begin an IPOs when they look at other firms in the same industry trading with high earnings and book-to-market multiplies. In other words, when shares are on average overvalued, companies have a greater probability of going public. Another result is given by Ritter and Welch (2002), who found a long-term underperformance of 23.4% over a three-year period between 1980 and 2001.

2.2.1. Fads and excessive optimism hypothesis

Intuitively, it can be claimed that IPO bad performance over a certain period reflects that investors were overoptimistic about the public information. This hypothesis explains bad long-run performance when investors are excessively enthusiastic about an IPO, and that their optimistic valuations will bias the result more than those that are pessimist. The assumption relies on that an optimistic valuation will have more weight than a pessimistic one. As the initial offering is further in time, the difference between these valuations will get closer to zero and, consequently, the price drops, which will finally result in underperformance. This hypothesis is suggested by Aggarwal and Rivioli (1990), Levis (1993) for UK IPOs, and Loughran and Ritter (1995).

[3] "Fads" in literature is attributed to irrational behaviour or temporary investment sentiments.

This is also named in the literature as the overreaction hypothesis. However, if market efficiency hypothesis holds, underreaction and overreaction occur with the same frequency, and underperformance will exist only temporarily. This idea is advocated by Fama (1998).

2.2.2. Agency hypothesis

Agents may play an important role in influencing the IPO process. Carter (1998) analysed the role of the underwriter reputation and its effect on both the level of underpricing and the long-run performance of IPOs. He argued that there was empirical evidence suggesting that underwriter reputation increased short-run returns and that the long-run performance was less negative.

Brav and Gompers (1997) study the long-run underperformance of venture-backed IPOs during 1972-1992 and find out that venture-backed IPOs outperform nonventure-backed IPOs, and also that venture-backed firms do not significantly underperform, while only the smallest nonventure-backed firms do. They concluded that underperformance was not a particular issue of IPOs.

2.3. Cyclicality in short-run performance

The last anomaly was examined firstly by Ibboston and Jaffe (1975), and later by Ritter (1984). Cyclicality indicates that the number of IPOs and the related size of underpricing have a strong cyclical pattern.

2.3.1. Changes in firm risk composition

Ritter (1984) discovered that in the year of 1980 the initial return was of 48.4% on average, whereas the mean from 1977 to 1982 (excluding 1980) was only 16.3%. This hot market was associated almost exclusively with natural resources firms. For other industries, this “hot issue” was barely noticed.

Furthermore, Ritter (1984) explained the hot issue by suggesting that the risk composition of firms going public throughout time is correlated with the presence of a hot market. Then, this would result in a higher percentage of risky companies entering the market at that moment. In other words, if there are some periods when a given sector is riskier, those periods will also have higher mean initial returns.

2.3.2. Windows of Opportunity

Besides the point that the IPO activity is associated with a high level of underpricing in a hot market, the presence also in those periods of poor long-term performance could provide an indication that companies are timing well their entrance in the stock exchange. Taking into consideration the advantage of being overvalued is referred in the literature as a “windows of opportunity” (Ritter, 1991). If indeed companies are taking advantage of market sentiment, by realizing that the sector is overvalued, and they go public, it is expected that these companies will perform poorly in the future. Investors´ misvaluation would be an opportunity for the firm to increase the volume of the IPO.

2.4. Hypothesis

Several scholars have faced the challenge of finding appropriate proxies to represent ex-ante and ex-post uncertainty. “Ex-ante” proxies refer to the variables that help to estimate the true value of underpricing before the event takes place, whereas “ex-post” proxies are related to the after-market characteristics. Another issue that needs to be mentioned is that uncertainty cannot be measured with a few set of variables since it can be affected by numerous factors. After discussing the existing literature and its empirical evidence, a set of hypothesis is established to test regarding the relationship between proxies of ex-ante and ex-post uncertainty and IPO initial returns.

Beatty and Ritter (1986), supported by the Winner´s curse theory of Rock (1986), assert that stock prices of smaller capitalized companies are more volatile and uncertain. Thus, they suggest that market size is negatively related to initial returns, which leads to the following hypothesis:

H$_1$: Market size is negatively related to the level of underpricing. (-)

Carter and Manaster (1990) argue that the prestige of underwriters prior to the IPO reduces the ex-ante uncertainty of an IPO. Beatty and Ritter (1986) affirm that underwriters have an incentive to maintain their reputation by not leaving too much money on the table because they are afraid to lose future potential customers. The following hypothesis is elaborated:

H$_2$: Underwriter reputation is inversely related to the level of underpricing. (-)

Furthermore, researchers have been using the variance of the after-market returns of IPOs, as it can be found in Ritter (1984) and Clarkson and Merkley (1994). The lower the liquidity, the higher the standard deviation of a given stock will be. Wasserfallen and Wittleder (1994) proposed the use of the standard deviation of returns of the first 20 days after the IPO as a variable with significant positive explanatory power. This is the first ex-post proxy to be mentioned in the present work. It will be as well incorporated in our testing analysis:

H_3: Standard deviation of first 20 after-market returns of IPOs is positively related to the level of underpricing. (+)

Another relevant variable is age. Company age, which is computed by the difference between the foundation date and the IPO date, is mentioned in Beatty and Ritter (1986), Ritter (1991), Barry, Murcarella, and Vetsuypens (1991), and Clarkson and Merkley (1994) has been negatively related to the level of underpricing. The valuation of a younger company is expected to be systematically uncertain, which leads to a higher degree of underpricing to compensate such risk. Additionally, Lowry, Officer, and Schwert (2010) observed an increase in volatility of initial returns when IPO companies are younger. The next hypothesis is introduced as:

H_4: Company age is negatively related to the level of underpricing. (-)

Similarly, Beatty and Ritter (1986) present that the use of gross proceeds was an appropriate proxy. Carter and Manaster (1990) show that the issue size is inversely related to the volatility of the initial returns. In the context of this thesis, the gross proceeds are defined as the number of shares offered in the primary market times the issue offer price. Related to this variable, it is also tested the significance of the number of uses of proceeds in explaining the ex-ante uncertainty of the firm value. Beatty and Ritter (1986) recommended this proxy, and they observed that as the information of the usage of proceeds increases, it requires more speculative investors to take part in the offering, and subsequently, the underpricing level will increase. The following two hypotheses are formulated this way:

H_5: Gross proceeds is negatively related to IPO underpricing. (-)

H_6: Number of uses of proceeds is positively related to IPO underpricing. (+)

Some scholars have noticed that a company undertaking an IPO when it is backed by a Venture Capitalist firm, underpricing will become more severe. This empirical evidence is supported by Barry (1990) and Ritter and Loughran (2002). The market reacts negatively when a venture capital does the monitoring role in a company going public. Mainly, this is because venture capitalists often take companies public remarkably soon, as they are pressured to achieve a return from their previous investment. Based on this theory, following hypothesis is formulated:

H_7: Venture-backed status at the time of the IPO is positively related to the degree of underpricing. (+)

According to what was commented above, the existence of IPO market cycles was reported for the first time in Ritter (1984). Moreover, there is empirical evidence that different sectors respond differently to their initial returns. Ritter (1984) found that gas and oil industry in the year of 1980 was with an enormous level of underpricing, as previously commented. In addition, Lowry, Officer, and Schwert (2010) perceived an increase in volatility of initial returns when IPO companies are tech companies. After 2014 of this work´s database, around 41% of IPOs occurred. Hence, we are going to test the presence of a hot market in the IPOs after the year of 2014 using a dummy variable.

H_8: The IPO period since 2014 is positively related to the level of underpricing. (+)

Lastly, Miller & Reilly (1987) support that trading volume in the after-market (ex-post proxy) indicates a higher uncertainty as regards to the stock´s true value. Hence, the last hypothesis is developed as follows:

H_9: The after-market trading volume will be positively related to the level of underpricing. (+)

3. Data

An extensive investigation has been done to construct the dataset. This section elaborates on which type of data has been used, for what purposes and how it was retrieved, but also what difficulties were faced while gathering the sample and what kinds of solutions were identified and opportunely applied.

For this work, a sample of 128 Fintech IPOs conducted in the US from 2005 to 2018 was assembled. The selection of companies for the fintech sample was indeed the first step before collecting financial data. The Fintech sector possesses an important aspect that needs to be mentioned: there is no NAICS[4], SIC, GICS or TRBC code to identify this specific sector. Hence, all the companies in the sample had to be extracted individually.

Primarily, a list of Fintech companies was composed using the database of Financial Technology (FT) Partners and their analysis. FT Partners disclose their research concerning the Fintech landscape and its fundamental key trends in their website[5], where they perform a deep analysis of Fintech IPOs in the US. They estimate that the number of IPOs in the US since 2005 is 134. In the present sample, financial information for 128 companies has been collected. Besides, several reports, articles, and other financial publications were used to refine the following dataset. In Appendix A, Table 1 presents an overview of the 128 US fintech companies.

Another key issue was to identify the time frame of this thesis. Several factors were used to select the suitable time period. A relevant factor was that before the financial crisis of 2008, an important portion of firms entered in the primary market. Due to that, three years before the crisis were included. Therefore, the time period was established to begin in 2005, which was also the starting point of FT Partners´ analysis, and to end in 2018.[6]

[4] Briefly, NAICS (North American Industry Classification System) is a code attributed to each company by the US government to classify the business of that company. For example, if real estate companies were of interest to this thesis, the first two digits that are going to be used to filter from other companies are “54”. Other codes like SIC, GICS and TRBC are used for the same purposes.

[5] https://www.ftpartners.com/fintech-research

[6] Data was retrieved until March 28th of 2018.

After defining a list of US fintech firms with IPOs between 2005 and 2018, the data required to run the analysis needed to be compiled. Hence, different financial databases like Thomson Reuters, Center for Research in Security Prices (CRSP) and Compustat were used, and their results were compared and double-checked to determine the reliability of the data[7]. Not a few times, the values of some variables needed to be corrected, namely, the date of foundation, IPO date and price close daily.

In addition, the use of some websites like Nasdaq/IPO[8] and Crunchbase[9] was crucial when obtaining variables like the number of shares offered, IPO date and offer price when the financial databases were missing data. Nevertheless, when essential data like the offer price, first 6 months of daily close prices and IPO date were not extracted the company was eliminated from the sample.

The variable prestige of the underwriter was assigned according to the dataset on IPO Reputation Rankings (1980-2015) on Jay Ritter´s website. If the underwriter has a score higher than 8.5, then, it will be classified as high prestige.[10]

As regards to stock returns, for each firm, returns were collected from their offering date until the third year[11] or its delisting date. A company´s status can become delisted due to an acquisition, merger, bankruptcy or if it seeks to change into a private company. The use of daily returns instead of monthly data has become more recurrent in the literature. Hence, daily security returns were retrieved to achieve a higher precision in measurement terms.

Finally, the data for the matching sample was extracted from COMPUSTAT´s entire US database. Only North American companies were used in this procedure. The matching sample approach is explained in Appendix B.

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7 For example, MasterCard Inc in Thomson Reuters has a first close price set at $4.6, instead of $46. This difference between both cases is overly important to be ignored. Thus, the approach chosen was very cautious and time-consuming,

8 https://www.nasdaq.com/markets/ipos/

9 https://www.crunchbase.com/

10 A dummy variable was adopted to construct this variable. If a given company has more than one underwriter, the one with the highest ranking will be the reference to assign the dummy variable.

11 Literature chooses up to three or five year when analyzing the long-run performance. The main reason for choosing three years was not losing too many observations.

4. Methodology

Given that this thesis concerns both short-run and long-run performance, a varied range of performance measures exist for their analysis. In this section, it will be provided a concise elaboration on the methods conducted in this dissertation. First, the short-run performance will be addressed and then the focus will be on the long-run performance.

4.1. Short-run stock performance

To analyse the phenomenon known as underpricing, the methodology is quite trivial. According to what scholars suggest, including Chambers and Dimson (2009) and Loughran and McDonald (2013), the short-run performance will be calculated as the percentage change of the first-day closing price after the IPO from the offer price, which indicates whether the offering was underpriced or overpriced:

$$1^{st}\ trading\ day\ return = \frac{Price_{close} - Price_{offer}}{Price_{offer}}$$

A positive percentage difference reveals that an IPO is underpriced and the company is leaving money on the table, whereas an IPO will be overpriced when the difference is negative.

After analyzing the empirical evidence of underpricing in this sample, the significance of ex-ante proxies and its explanatory power on the underpricing level is tested. Appendix C shows the descriptive statistics of the main variables that are going to be used for these tests.

In line with Clarkson (1994), where several ex-ante proxies for uncertainty helped to explain the level of underpricing in 420 US IPOs, this work reconsiders that IPO underpricing is predicted by selected proxies of ex-ante uncertainty. More recently, Loughran and McDonald (2013) conducted a similar analysis.

The first trading day return will be the dependent variable in a multiple regression analysis, which is going to be conducted to estimate the relationship between several ex-ante proxies and the dependent variable. The Ordinary Least Squares (OLS) method is going to be performed to estimate the unknown parameters, which can be described in the following standard form:

$$Y_i = \alpha_{i+}\beta_1 X_{1i+\cdots+}\beta_h X_{hi} + \mu_i$$

In which the dependent variable Y_i is defined as the first day return of firm i. This is regressed against all proxies of ex-ante uncertainty. Hence, on the left hand side of this model, it is placed the degree of underpricing for every fintech that issued an IPO between 2005 and 2018. The intercept is denoted as α_i, and X_1 to X_h are the independent variables, with their corresponding coefficient given by β_1 to β_h.

To illustrate the results in a clarified manner, three models are going to be classified according to the regression variables contained in each. Below, Model 1 presents all financial variables: *Stdv* refers to the standard deviation of the 20 first trading days after the IPO, *ln(Proceeds)* is the logarithm of the gross proceeds from the sale of the initial offering, *ln(MktCap)* is the logarithm of the firm value, *ln(Rev)* indicates the logarithm of the firm´s revenues and *TdVol* is the trading volume at the IPO date. Thus, the first regression is expressed in the following manner:

$$1^{st} day\, return_i = \alpha_i + \beta_1 Stdv_i + \beta_2 ln(Proceeds)_i + \beta_3 ln(MktCap)_i + \beta_4 ln(Rev)_i$$
$$+ \beta_5 TdVol_i + \mu_i$$

For Model 2, the signalling variables, which are the variables that presumably are signalling the firm value to investors, are added to the variables introduced primarily in Model 1. Model 2 is defined as:

$$1^{st} day\, return_i = \alpha_i + \beta_1 Stdv_i + \beta_2 ln(Proceeds)_i + \beta_3 ln(MktCap)_i + \beta_4 ln(Rev)_i$$
$$+ \beta_5 TdVol_i + \beta_6 Rank\_U_i + \beta_7 OwnerRet_i + \beta_8 VentBack_i + \beta_9 Uses\_P_i + \mu_i$$

Where *Rank_U* is a dummy variable for the underwriter prestige, *OwnerRet* refers to the retention ownership[12] at the IPO date, *VentBack* is a dummy variable identifying the existence of a venture capital firm before the company is taken public, and *Uses_P* is defined as the number of uses of proceeds that are mentioned in the firm´s prospectus.

Finally, Model 3 is constructed by including the remaining two variables: log of company age, *ln(Age),* and a dummy variable testing the existence of a hot market since 2014, defined as *Hot*.

[12] Retention ownership is defined as the number of shares offered divided by the number of shares outstanding

$$1^{st} day\, return_i = \alpha_i + \beta_1 Stdv_i + \beta_2 ln(Proceeds)_i + \beta_3 ln(MktCap)_i + \beta_4 ln(Rev)_i + \beta_5 TdVol_i + \beta_6 Rank\_U_i + \beta_7 Owner_i + \beta_8 VentBack_i + \beta_9 Uses_i + \beta_{10} ln(Age)_i + \beta_{11} Hot_i + \mu_i$$

Appendix E summarily describes all independent variables of the 3 models above.

4.2. Long-run stock performance

Event studies, which were introduced by Fama (1969), are an empirical methodology used to investigate the stock performance after a given corporate event occurs. The latter are used to test market efficiency[13]. Under a market efficient framework, it is not conceivable to have investors systematically gaining abnormal returns and to observe stock patterns. In a concise manner, whether we have market efficiency, or we have price anomalies.

Concerning long-run methodology, Lyon, Barber, and Tsai (1999) described the analysis of long-run abnormal returns as “treacherous”, and still today, literature looks to the long-horizon analysis with “extreme caution” (Kothari and Warner, 1997) and observes always its serious limitations.[14] Overall, research on event studies does not agree on which methodology yields most accurate and robust results.

Currently, the dilemma faced in recent literature is explained by the joint-test[15] problem: rejecting the hypothesis of abnormal returns might not be due to the existence of mispricing but, instead, due to misspecification. Thus, this analysis pretends not only to present results but also to outline the benefits and disadvantages of the methodology applied. Nonetheless, it is not of the scope of this master thesis to reach conclusions of which method yield better empirical results.

For this dissertation, performance is defined as the percentage change in a company´s market capitalization measured by its daily closing price over a given period T on a monthly basis, and its difference to an expected return, known in the literature as the “normal” return.

[13] In an efficient market, share prices react immediately to all the information available.

[14] As affirmed by Fama (1998), “all models for expected returns are incomplete descriptions of the systematic patterns of average returns”. This is in contrast with short-run analysis, which is much simpler to be applied and interpreted. It is often utilized the expression used by Fama (1991) to classify short-horizon event studies as the “cleanest evidence we have on efficiency”.

[15] See Kothari and Warner (2007) for further development.

Three different ways of measuring normal returns are computed in this analysis: using a model (Fama-French three-factor and the Carhart four-factor models), a reference portfolio[16] and a control firm approach.

Two major approaches are proposed in the literature to study the long-run behaviour of stocks: the event-time approach and the calendar-time approach. Within the event-time approach, two variants are going to be applied: the cumulative abnormal return measure (CAR) and the Buy and Hold abnormal return measure (BHAR). Alongside this, the calendar-time approach is divided into two main computations as well: the Fama-French three-factor model together with the Carhart four-factor model, and the mean monthly abnormal returns.

For this particular work, a year is defined as 12 months with 21 trading days each month (21x12 = 252 days). The long-run stock performance will be conducted over three years after the event date.

4.2.1. Event-time approach

According to the event-time approach, stock performance is measured by bundling all returns for a given time frame after the IPO. For a portfolio, all stocks are set at the same starting point, regardless of their calendar event month[17]. Next, a brief description of the computation of Cumulative Abnormal Returns (CAR) and Buy-And-Hold Abnormal Returns (BHAR) is made. In Appendix D, the test statistics that were computed for these two methods are succinctly explained.

4.2.1.1. Cumulative Abnormal Returns (CAR)

The cumulative abnormal return method is the first methodology to be considered since is one of the first approaches to be implemented in the long-horizon study for IPOs performance (Ritter, 1991). Firstly, it is convenient to define abnormal returns:

$$ar_{it} = r_{it} - r_{mt}$$

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16 Nasdaq, S&P 500, and CRSP Nasdaq cap-based market indices are used in the present thesis.

17 Suppose that a given portfolio consists exclusively of two companies, namely *alpha* and *beta*, and their event dates go back to January and February of 2008 respectively. In this approach, the exact months are disregarded, and both companies start at the same moment t=0.

The abnormal return is calculated by subtracting the actual sample stock return by the normal return, where ar_{it} being the abnormal return in month t for stock i, r_{it} as the return for stock i in month t and r_{mt} as the normal return for month t.

The average abnormal return for all n stocks in our portfolio in IPO month t is calculated as the equally-weighted or value-weighted average[18] of benchmark-adjusted returns:

$$AR_t = \sum_{i=1}^{n} w_{it} * ar_{it} \; where \; w_{it} = \begin{cases} w_{it} = \dfrac{MV_i}{\sum MV} \\ \hline w_{it} = \dfrac{1}{n} \end{cases}$$

CARs are computed by aggregating all average abnormal returns (AR_t) after the IPO date takes place until T, and it is defined as:

$$CAR_{1toT} = \sum_{t=1}^{T} AR_t$$

If the CAR delivers a positive value, the portfolio has performed better than the benchmark for the period of time T. Note that for this analysis when a firm is delisted, returns are truncated for the future periods.

Barber and Lyon (1997) identified three biases that CARs suffer: firstly, a measurement bias that consists of CARs being biased predictors of long-run BHARs. Secondly, a new listing bias is referred, which suggests that new firms are incorporated in reference portfolios. Finally, a skewness bias arises because it is common to identify a firm in the sample achieving an abnormal return greater than 100%, but really unusual to find a return of a market index higher than 100%. Thus, this implies that abnormal returns are positively skewed. In addition, CARs ignore compounding, as a result, they do not give a real representation of the investment strategy since the portfolio is constantly being rebalanced at the end of each period.

[18] When computing value-weighted abnormal returns, for the weight of each company their market capitalization at the IPO date is used.

4.2.1.2. Buy-and-Hold Abnormal Returns

The alternative and more popular measurement of abnormal returns in event-time studies are the buy-and-hold returns (BHARs), which geometrically compounds individual share price returns over the holding periods.

An interesting feature of calculating buy-and-hold returns is that it better represents investors' real experience rather than using a periodic rebalancing, as in the case of cumulative abnormal returns. BHARs rely on the assumption that the investors purchase a given asset at the starting point, hold it for a period and then sell it.

Barber and Lyon (1997) in their paper outline that CARs suffer from measurement bias, new listing bias, and skewness bias, while BHARs are subject to new listing bias, skewness bias, and rebalancing bias. Still, they prefer the latter. Moreover, they highlight that the control firm approach solves the new listing bias, the rebalancing bias, and the skewness bias. The control firm approach yields well-specified test statistics. The computation is as follows:

$$BHAR_i = \prod_{t=1}^{T}(1 + r_{it}) - \prod_{t=1}^{T}(1 + r_{bt})$$

Where r_{it} is the return for stock i in month t and r_{bt} as the benchmark return for month t. T is the holding period of the investment, including the event month. The average monthly BHAR is computed whether with equal-weighed or value-weighted, just as for the CAR method. Its expression is given by:

$$BHAR_{1\ to\ T} = \sum_{i=1}^{N} w_{it} * BHAR_{1\ to\ t} \text{ and } w_{it} = \begin{cases} w_{it} = \frac{MV_i}{\sum MV} \\ w_{it} = \frac{1}{n} \end{cases}$$

Finally, Mitchell and Strafford (2000) affirm that the presence of cross-sectional dependence of abnormal returns contributes to accept the hypothesis of the existence of non-zero abnormal returns. This issue is solved when applying the calendar-time approach.

4.2.2. Calendar-time approach

To enlarge the spectrum of this dissertation, the calendar-time approach will be incorporated. This method was initially introduced by Jaffe (1974) and Mandelker (1974), and they suggest the development of a portfolio of share price according to their calendar months to solve the problem of cross-sectional dependence of returns. This methodology differs from event-time in the sense that once a given time frame is defined, share returns are summed up in accordance to their calendar month.

Barber and Lyon (1999) promote the calendar-time methodology for two main aspects: the first one was already mentioned and is that it solves cross-sectional dependence of securities abnormal returns. The second one is that is robust in non-random samples. They advocate the non-randomness of sample firms given that the researcher did not pick up a sample randomly; instead, he filtered firms according to the event study.

4.2.2.1. Fama-French Three-Factor Model

Fama (1998) support the use of the model proposed in Fama and French (1993) due to its ability to capture precise stock price patterns, without neglecting that the model still suffers from mispricing[19]. Although this model is controversial concerning its accuracy to identify the features of returns, it is still performed as an option to measure and test long-horizon share performance due to the elimination of cross-sectional returns.

$$R_{pi} - R_{bi} = \alpha_i + \beta_i\left(R_{mi} - R_{fi}\right) + \delta_i SMB_i + \mu_i HML_i + \varepsilon_i$$

Where $(R_{pi} - R_{bi})$ is the dependent variable, which is composed of the event portfolio return, R_{pi}, in excess of the 1 month Treasury-bill return, R_{bi}. The independent variables in this regression of which coefficients will be estimated are the following: $\left(R_{mi} - R_{fi}\right)$ as the market portfolio; SMB_i as the difference in value-weighted return of small market cap and big market cap firms; and HML_i as the difference of value-weighted returns of high book-to-market and low book-to-market companies.

[19] It is mentioned in Fama (1998) as the "bad-model" issue. The "bad-model" appears when using a given benchmark to reproduce expected returns. This is always a simplification of reality and does not capture all factors. Fama (1998) asserts that "bad-model problems are unavoidable, and they are more serious in tests on long-term returns"

ε is defined as the error term which explains those returns that are not captured by the three-factor model. The intercept α is the variable used to test the existence of non-zero abnormal returns. Nevertheless, residuals can be heteroskedastic because of variation of the number of firms across event months. To solve this issue, White standard errors can be computed.

Loughran and Ritter (2000) contest the usage of this model to capture abnormal returns for three particular motives: firstly, they suggest that it is a big simplification attributing equal weights in event months regardless of the months of "hot" activity; next, they challenge the idea of conducting equal weights disregarding if a firm is small or big. This creates an overestimation of abnormal returns compared with the usage of a value weighting approach; last of all, using factors without purging the returns of sample firms leads to a contamination bias.

4.2.2.2. Carhart Four-Factor Model

For the purpose of introducing the conclusions reached by Jegadeesh and Titman (1993)[20], Carhart (1997) expands the model explained in Fama and French (1993) into a four-factor approach, in which an additional factor to capture the momentum phenomenon is introduced. Carhart backs the idea that portfolio performance is persistently explained by the one-year momentum factor.

$$R_{pi} - R_{bi} = \alpha_i + \beta_i\left(R_{mi} - R_{fi}\right) + \delta_i SMB_i + \mu_i HML_i + \varphi_i UMD_i + \varepsilon_i$$

In which UMD_i is the difference between high past returns and low past returns stocks. Ang and Zhang (2004) concluded that the four-factor model leads too many rejections when compared to the better well-specified three-factor model.

[20] They found positive abnormal returns when applying an investment strategy that consists in buying stocks that performed well and selling stocks with crummy performance for the three to twelve months.

4.2.2.3. Mean Monthly Calendar-Time Abnormal Return

Lyon, Barber, and Tsai (1999) and Fama (1998) heavily suggest the introduction of mean monthly calendar-time abnormal returns due to the presence of cross-sectional returns.

The abnormal return is defined as the difference of each stock price return and the corresponding benchmark return in calendar month t. It is expressed as follows:

$$ar_{it} = r_{it} - r_{mt}$$

Then, it is performed the summation of all stocks i in the sample with their respective weights for each calendar month t, in a similar fashion as previously done for CARs and BHARs.

$$CTAR_t = \sum_{i=1}^{n} w_{it} * ar_{it} \text{ Where } w_{it} = \begin{cases} w_{it} = \frac{MV_i}{\sum MV} \\ w_{it} = \frac{1}{n} \end{cases}$$

A yearly calendar-time abnormal return (YCTAR) is calculated for all years of the sample´s time period, by summing all calendar month for the respective year. It is given by:

$$YCTAR = \sum_{t=1}^{12} CTAR_t$$

As well, a final monthly grand mean for all T months (MCTAR) is computed in the following way:

$$MCTAR = \sum_{t=1}^{T} CTAR_t / T$$

To test the existence of abnormal returns during the period of time T, the conventional t-test is conducted:

$$t = \frac{MCTAR}{\sigma(CTAR_t)/\sqrt{T}}$$

Where *MCTAR* is the grand mean calendar monthly abnormal returns, and $\sigma(CTAR_t)$ is the standard deviations of abnormal returns for the portfolio of n companies for all T periods.

5. Results

After considering the present literature and methodology to be applied in abnormal returns, this chapter introduces and discusses the results obtained for the US fintech IPOs. First of all, section 5.1 illustrates the main results for the short-run performance, and after, section 5.2 examines the outcome of the long-run behaviour of our fintech sample.

5.1. Short-run performance of US fintech

Following what was presented in Chapter 2, past empirical evidence supports that average initial returns are positive. Accordingly, in this dissertation about US fintech IPOs, the underpricing phenomenon is unambiguously identified. First, this section presents precisely the level of underpricing and its significance, and then it provides the outcome of the cross-sectional regression described above.

5.1.1. Underpricing level

In Figure 1, the plot of annual volume and the average initial return on IPOs from the beginning of 2005 until February of 2018[21] is illustrated.

From this figure, it can be concluded that, although reasonably volatile, underpricing is fairly constant across the years. It is not possible to notice a clear correlation between volume and underpricing for this sample. Probably, if the number of observations was larger, this relation would become amplified and more apparent. However, regarding the initial 5 years of the sample´s time period, this correlation is verified. On the other hand, for the rest of the sample´s years, it looks inconclusive.

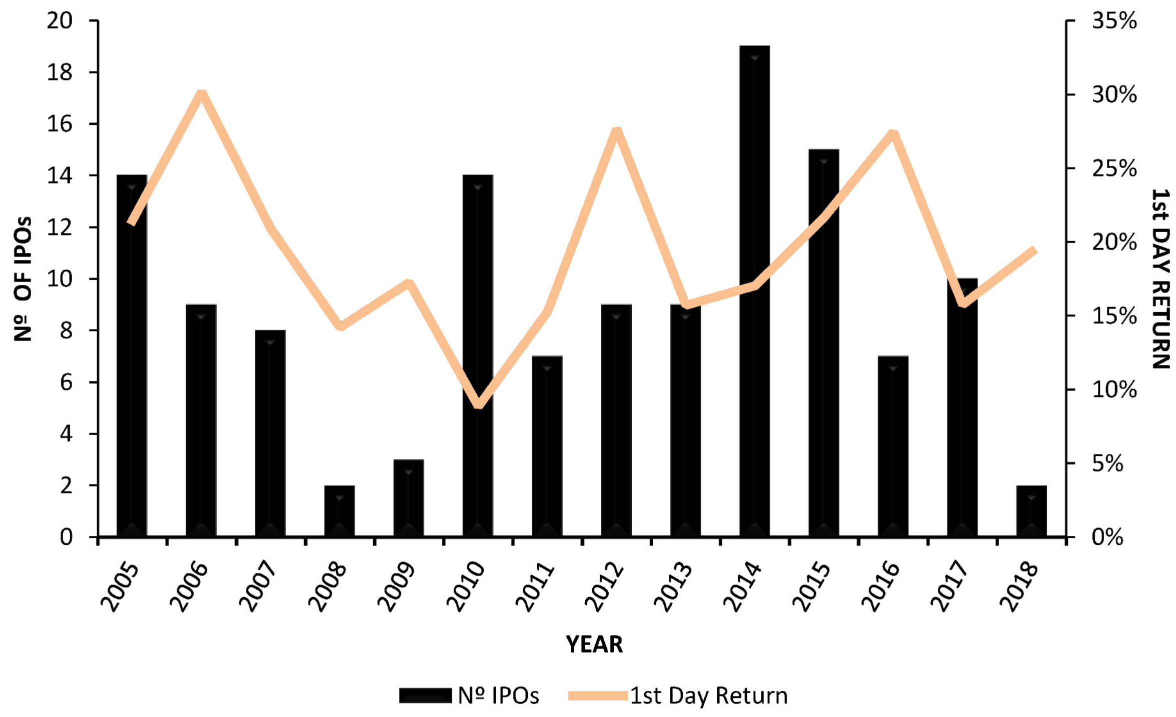
It is possible to observe three peaks above 25% for the level of underpricing. For the years of 2006, 2012, and 2016 the level of underpricing is 30.16%, 27.66%, and 27.45%, respectively. Turning to the number of IPOs executed, it is relevant to mention the peak of 14 IPOs in 2010, after the financial crisis. The maximum volume of IPOs in a given year was 19 in 2014. In addition, it is relevant to notice that during the financial crisis, and also in the subsequent year of 2009, the number of IPOs decreased dramatically, with only 5 IPOs

[21] For 2018 only two months are considered, therefore, it cannot be significant to take conclusions regarding the volume of that precise year.

completed during those two years. This decreasing trend was followed by a decline of initial returns, although with a lower magnitude comparing with the sharp decline of IPO volume. Ritter (2017) registered an average initial return of 5.7% in 2008, whereas, in our sample, a mean initial return of 14.2% was recorded. For the present thesis, underpricing varies mainly around 10% and 30%.

Figure 1 – Volume and Initial Returns of Fintech IPOs by cohort year

This plot presents the volume and the first trading day returns for 128 fintech companies between 2005 and 2018. Recall that initial returns are computed as the percentage change of the first-day closing price from the offer price.



In Appendix F, two tables regarding the level of underpricing can be found: Table 2 and Table 3. In Table 2, it is shown that the average initial return for all sample periods is of 19.35%, which is statistically different from 0. This is one of the most relevant results of this thesis. According to the research made by Ritter (2017), between 2005 and 2016 the mean underpricing level is around 13.58%[22]. At this point, not much can be affirmed regarding fintech IPOs compared to other industries without losing accuracy.

[22] This value is an equal-weighted average of the yearly results of underpricing for Ritter´s sample during 2005 and 2016

Finally, Table 3 contains the test statistics for the significance of the underpricing level across the sample´s years. It must be considered that in some cases, where the IPO volume is small, some test statistics are not significant due to a high standard deviation. With the exception of 2015, whenever the number of IPOs is above 9 for a given year, the test statistic will reject the null of the underpricing level being equal to 0. For 2005, 2014, and 2017 the mean initial return is significant for a 99% confidence interval. Furthermore, for the 8 years of this sample, the underpricing is significant with at least a 10% significance level.

5.1.2. Cross-sectional regressions

Afterwards, the cross-sectional regression analysis of underpricing will be conducted. Below, in Table 5, the coefficients and test statistics are observed for each variable of all three regressed models. Model 1 includes financial variables that were found relevant in past literature. For the US fintech industry, ln(MarketValue) and ln(Proceeds) are shown to be highly significant in explaining underpricing. Only the latter is according to the ex-ante uncertainty hypothesis: the gross proceeds is negatively associated with the level of initial returns.

However, the two ex-post variables that were here introduced, namely the standard deviation of first 20 trading returns and the trading volume, are non-significant and with contradictory signs. Moreover, ln(Revenues) was tested and appears to be significant at a 95% confidence level. Ln(Revenues) exhibits a negative coefficient, meaning that the amount of revenues reduces the level of underpricing. As revenues increases for a given company, initial return after the IPO is going to be reduced, on average and *coeteris paribus*.

Model 2 contains the same variables of Model 1 although also adds the signalling variables. Adding signalling variables improves the explanatory power of the regression. The R^2 yields 37.5%, and when comparing to Model 1, it experiences an increment of +5.35%. This suggests the importance of signalling variables in explaining the underpricing level of the fintech sample. For this second regression, ln(MarketValue) and ln(Proceeds) remain very significant. Additionally, being venture-backed is deeply significant for fintechs and corroborates previous research. It is viewed as a bad signalling by the investors' community and is punished with higher underpricing. Other signalling variables such as the number of uses of proceeds and the underwriter reputation are marginally positive. The latter is even in contradiction with the initial guess made in the previous section. Ownership retention is also non-significant for the fintech sector.

Table 5 – Regressions of Initial Returns

A sample of 128 fintech companies is used for these regressions. The first trading day return is the independent variable (calculated as the percentage change of the first-day closing price from the offer price). Entries are the coefficients, and in parenthesis the t-statistics. The test performed is a two-tailed test statistic, which is computed for 90%, 95% and 99% confidence levels. Accordingly, one, two, or three asterisks refer to significance at 10%, 5%, and 1%, respectively.

Variable	Model 1	Model 2	Model 3
Intercept	-0.61	-1.22***	-1.23***
	(-1.56)	(-2.62)	(-2.63)
Std dev (first 20 days)	-1.3	-2.94**	-2.73*
	(-1.03)	(-2.06)	(-1.91)
Ln(Proceeds)	-0.14***	-0.11**	-0.12***
	(-3.99)	(-2.43)	(-2.63)
Trade Volume	-0.01	-0.03	-0.04
	(-0.38)	(-1.16)	(-1.44)
Ln(MarketCap)	0.21***	0.20***	0.22***
	(7.09)	(6.09)	(6.28)
Ln(Revenues)	-0.04**	-0.02	-0.02
	(-2)	(-1.19)	(-1.1)
Underwriter reputation		0.02	0.04
		(0.41)	(0.61)
# Uses of Proceeds		0.01	0.02
		(1.21)	(1.3)
Venture-Backed		0.13***	0.14***
		(2.71)	(2.72)
Ownership Retention		0.04	0.07
		(0.47)	(0.89)
Ln(Age)			0.02
			(0.7)
2014+ dummy			-0.06
			(-1.31)
R^2	0.318	0.3715	0.318
# observations	128	128	128

Furthermore, the standard deviation of the 20 first returns presents statistical significance at a 5% significance level, although its sign differs from what was expected from literature. Additionally, ln(Revenues) is no longer significant compared to Model 1.

Finally, Model 3 adds two more variables: a dummy variable testing the presence of a hot market after 2014 and a log variable of company age. These two variables are non-significant, and the age variable does not agree with literature made on ex-ante proxies. With these two new variables, the model loses the explanatory power gained initially when going from Model 1 to Model 2. These results indicate that Model 2 is the best model to explain the level of underpricing. In the end, just 3 out of 9 literature hypotheses are verified for our sample. There is no evidence that the ex-ante uncertainty theory holds.

In Appendix G, the correlation matrix of all independent variables, tests for multicollinearity and Model 3 regressed with robust heteroskedastic standard errors are illustrated. The variance inflation factor (VIF) test indicates the size of an upward inflation impact on standard errors. Scholars suggest different rules for setting a maximum value for admitting a given VIF. The more conservative ones, like Ringle et al. (2015), set a maximum of 5, and other such as Hair et al. (1995), established 10. In this sample, only one variable is slightly above, and that is ln(Proceeds), with 5.47 and 5.62 for Model 2 and Model 3, respectively. In addition, Model 3 was regressed with standard errors robust to heteroskedasticity. The difference regarding results when compared with the first OLS regression is small, which indicates that heteroskedasticity might not be a problem.

5.2. Long-run performance of US fintech

After conducting the analysis on the performance for the first day of the entire sample, this thesis goes on presenting the main results of the long-run performance. This analysis begins with the examination of the event-time approach, which will be followed by evaluating the calendar-time approach.

5.2.1. Event-time results

This sub-section presents the behaviour of fintech stocks when applying the two event-time methods that were conducted in this work: CARs and BHARs.

5.2.1.1. Cumulative Abnormal Return (CAR)

Table 7 illustrates the computations of CARs for the sample companies using four different benchmarks. Moreover, they were computed using EW and VW approaches for three year period to identify the difference in the behaviour of smaller and larger firms in the fintech sample.

As it can be noticed, after computing three-year CARs there is empirical evidence that the fintech portfolio is underperforming two of four benchmarks used: S&P and Nasdaq. Although these two benchmarks deliver high negative abnormal returns, it cannot be concluded that they are systematically reaching negative abnormal returns due to a high standard deviation. In fact, in overall terms, there are few statically significant abnormal returns when applying the CAR method. Also, if we employ a different expected return as the control firm or use the CRSP cap-based portfolio for a medium size company as a market index high negative abnormal returns vanish completely, and in some scenarios, positive abnormal returns are documented. Additionally, when changing from EW to VW, it seems to attribute greater negative return for S&P and Nasdaq market indices.

Table 7 - Cumulative Abnormal Return for US Fintech IPOs

This table presents fintech cumulative abnormal returns against four different benchmarks. The sample is composed of 128 fintech companies from 2005 until 2018. For each IPO, the returns are computed by monthly compounding daily price returns. The long-run performance is analysed until the 36th month anniversary after the initial offering or until the delisting date. Entries are the coefficients, and in parenthesis the t-statistics. The test performed is a two-tailed test statistic, which is computed for 90%, 95% and 99% confidence levels. Accordingly, one, two, or three asterisks refer to significance at 10%, 5%, and 1%, respectively.

Benchmarks	**1-month**	**3-month**	**6-month**	**1-year**	**2-year**	**3-year**[23]
	Panel A: Equal-Weighted Cumulative Abnormal Returns					
NSQ EW	-0.68%	-1.16%	2.01%	3.79%	4.30%	-13.18%
	(-0.5086)	(-0.4163)	(0.6328)	(0.7955)	(0.5497)	(-0.9810)
NSQ medium firm[24]	0.17%	1.99%	0.50%	1.78%	0.14%	1.06%
	(0.1386)	(1.0512)	(0.2942)	(0.9659)	(0.0774)	(0.4406)
S&P EW	-0.35%	0.56%	3.09%	5.53%	7.13%	-6.24%
	(-0.2156)	(0.2310)	(1.0266)	(1.1750)	(0.9163)	(-0.4658)
Control Firm	-0.67%	1.74%	-0.11%	1.53%	1.26%	-1.09%
	(-0.3524)	(0.6863)	(-0.04490)	(0.5455)	(0.5019)	(-0.2362)
	Panel B: Value-Weighted Cumulative Abnormal Returns					
NSQ EW	2.43%*	1.67%	-1.34%	1.72%	4.76%	-21.98%
	(1.8274)	(0.5995)	(-0.4231)	(0.3600)	(0.7018)	(-1.6359)
NSQ medium firm	2.91%**	3.12%	-2.57%	5.51%***	0.93%	2.04%
	(2.3760)	-1.6478	(-1.5068)	(2.9893)	(0.5266)	(0.8498)
S&P EW	2.58%**	3.77%	0.84%	3.19%	9.18%	-13.67%
	(2.0415)	(1.5486)	(0.2780)	(0.6776)	(1.1803)	(-1.0210)
Control Firm	-0.06%	6.11%**	0.48%	-1.46%	1.10%	0.81%
	(-0.0310)	(2.4111)	(0.1954)	(-0.5195)	(0.4403)	(0.1756)

[23] After three years, 81 companies remain listed.

[24] This is a CRSP cap-based portfolio for Nasdaq companies. Portfolios are constructed by creating size deciles for NYSE companies. This thesis named “medium” to the decile 5, and “large” and “small” to decile 1 and 10, correspondingly. Then, each Nasdaq company will correspond to a given NYSE decile according to its market value. This benchmark is only available until the end of 2017.

Next, in Figure 2 and Figure 3, CARs are illustrated either using EW or VW methods.

Figure 2 – Equal-Weighted Cumulative Abnormal Returns for US Fintech IPOs

This plot presents the average Cumulative Abnormal Returns for an EW portfolio of the US fintech industry from 2005 to 2018, with monthly rebalancing. Four CARs are observed: 1) Cumulative raw returns (no adjustment), 2) Control firm approach, 3) S&P 500 equal-weighted market index, and 4) Nasdaq equal-weighted market index. Month zero is the beginning of the return interval.

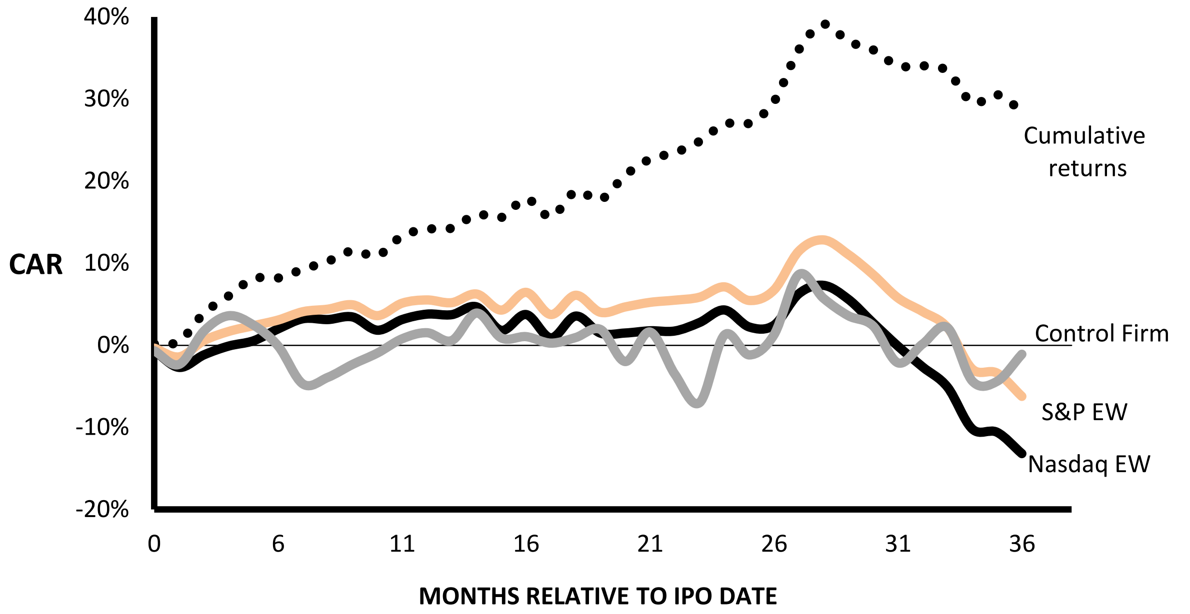
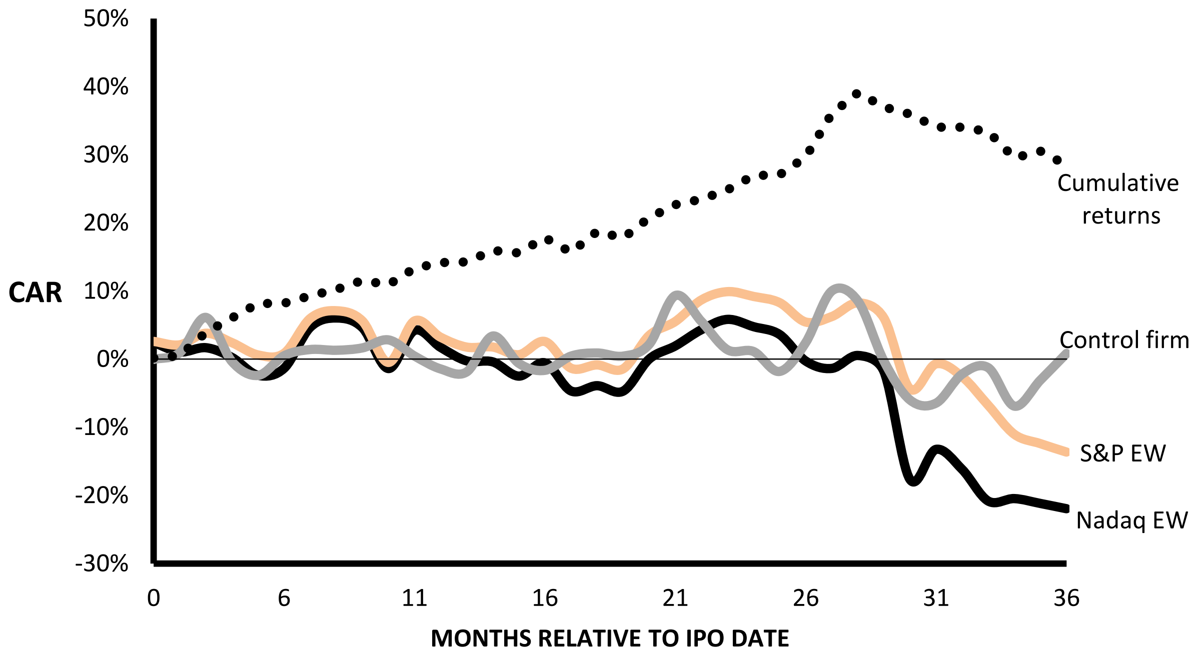


Figure 3 – Value-Weighted Cumulative Abnormal Returns for US Fintech IPOs

This plot presents the average Cumulative Abnormal Returns for a VW portfolio of the US fintech industry from 2005 to 2018, with monthly rebalancing. Four CARs are observed: 1) Cumulative raw returns (no adjustment), 2) Control firm approach, 3) S&P 500 equal-weighted market index, and 4) Nasdaq equal-weighted market index. Month zero is the beginning of the return interval.



The main result from these two figures consists in the persistence of positive (although small) abnormal returns since month 0 until approximately the 28th anniversary related to the IPO date. And after that, the performance is strongly poor, especially for the case of the value-weighted approach. Empirically, it is difficult to explain this trend. If the defence of the market efficient hypothesis is the driver of the analysis, a researcher would state that the market is adjusting in the third year for yielding positive abnormal returns in the first periods after the IPO. He will argue that this was due to temporary overreaction of the fintech sector. However, it is difficult to explain how fintech systematically outperform the market for the first 2 years after the IPO.

Literature, as previously discussed, does not favour much the use of CARs and tries to rely more on other methods. Thus, the analysis of long-run performance will continue to other approaches in order to try to achieve more reliable and clear results.

5.2.1.2. Buy-And-Hold Abnormal Return (BHAR)

The same structure of the analysis done with CARs is to be conducted with BHARs. Furthermore, at the end of this section, besides the conventional t-statistics to test whether the mean abnormal return is equal to zero, two non-parametric tests were conducted for both CARs and BHARs: Fisher´s Sign Test and the Wilcoxon sign-rank test.

Comparing with the CAR approach, Table 8 shows a steady increase in the magnitude of positive abnormal returns when computing BHARs. Also, it is detected statistical significance in an increased number of cases. Although the value-weighted computation continues showing to yield negative abnormal returns for S&P and Nasdaq market indices, the equal-weighted measures are no longer showing underperformance in the long-run when BHARs are computed.

Equal-weighted BHARs for fintechs are producing more significant returns than the equivalent method for CARs. At the end of the third year, the S&P, the control approach, and the CRSP Nasdaq medium firm yield 9.93%, 27.18%, and 31.99%, respectively. It is important to point out that during the three years’ time period, there are several points in time where positive abnormal returns present statistical significance, especially in Panel B. On the other hand, negative abnormal returns are showing significance only in two cases: for Nasdaq and S&P in the third-year VW approach. Although Panel B shows a strongly negative abnormal return for these two cases (for instance, the Nasdaq VW reaches -32.30%), in overall terms, there is a clear inclination of BHARs towards delivering "overperformance" instead of the anomaly of underperformance that is documented in the literature. Overall, there is no strong evidence of underperformance after applying the event-time approach.

Table 8 – Buy-And-Hold Abnormal Return for US Fintech IPOs

This table presents fintech buy-and-hold abnormal returns against four different benchmarks. The sample is composed of 128 fintech companies from 2005 until 2018. For each IPO, the returns are computed by monthly compounding daily price returns. The long-run performance is analysed until the 36th month anniversary after the initial offering or until the delisting date. Entries are the coefficients, and in parenthesis the t-statistics. The test performed is a two-tailed test statistic, which is computed for 90%, 95%, and 99% confidence levels. Accordingly, one, two, or three asterisks refer to significance at 10%, 5%, and 1%, respectively.

Benchmarks	1-month	3-month	6-month	1-year	2-year	3-year
	Panel A: Equal-Weighted Buy-And-Hold Abnormal Returns					
NSQ EW	-0.68%	-1.44%	0.92%	5.88%	14.88%	0.06%
	(-0.5085)	(-0.5193)	(0.2848)	(1.2328)	(1.64)	(0.006)
NSQ medium firm	0.17%	6.73%**	5.36%*	14.99%***	26.23%***	31.99%***
	(0.1386)	(2.4920)	(1.8425)	(3.0912)	(2.8998)	(3.4226)
S&P EW	-0.35%	0.33%	2.08%	7.84%*	18.40%**	9.93%
	(-0.2768)	(0.1352)	(0.6795)	(1.6614)	(2.0405)	(1.0912)
Control Firm	-0.67%	0.40%	-0.88%	0.57%	17.40%	27.18%**
	(-0.3524)	(0.1294)	(-0.1840)	(0.0834)	(1.5739)	(2.1175)
	Panel B: Value-Weighted Buy-And-Hold Abnormal Returns					
NSQ EW	2.43%*	2.05%	-1.04%	5.61%	13.02%	-32.54***
	(1.8218)	(0.7396)	(-0.3226)	(1.1770)	(1.4326)	(-3.5131)
NSQ medium firm	2.91%**	9.62%***	6.55%**	13.97%***	34.08%***	11.30%
	(2.3760)	(3.5610)	(2.2503)	(2.8802)	(3.7677)	(1.2094)
S&P EW	2.58%**	4.18%*	1.10%	7.00%	19.05%**	-19.72%**
	(2.0415)	(1.7290)	(0.3597)	(1.4821)	(2.1122)	(-2.1659)
Control Firm	-0.06%	6.04%**	1.38%	9.92%	28.55%**	14.49%
	(-0.0310)	(1.9558)	(0.2908)	(1.4513)	2.5811	(1.1288)

From Figure 4 and Figure 5 below, the long-run patterns of BHAR for both EW and VW are identified: while the EW portfolio performs positively throughout the three year period, the VW portfolio for the Nasdaq and S&P benchmarks start reversing its positive initial trend around the 25th month of our analysis. For the latter, positive performance is observed only until the second year, with the exception of the control firm approach, which achieves consistent positive performance for both EW and VW methods.

This difference between EW and VW indicates that a few big size companies in this sector experienced poor performance after the second year, and they are driving the portfolio to perform poorly as well.

Figure 4 – Equal-Weighted Buy-And-Hold Abnormal Returns for US Fintech IPOs

This plot presents the average Buy-And-Hold Abnormal Returns for an EW portfolio of the US fintech industry from 2005 to 2018. Four BHARs are observed: 1) Compounding raw returns (no adjustment), 2) Control firm approach, 3) S&P 500 equal-weighted market index, and 4) Nasdaq equal-weighted market index. Month zero is the beginning of the return interval.

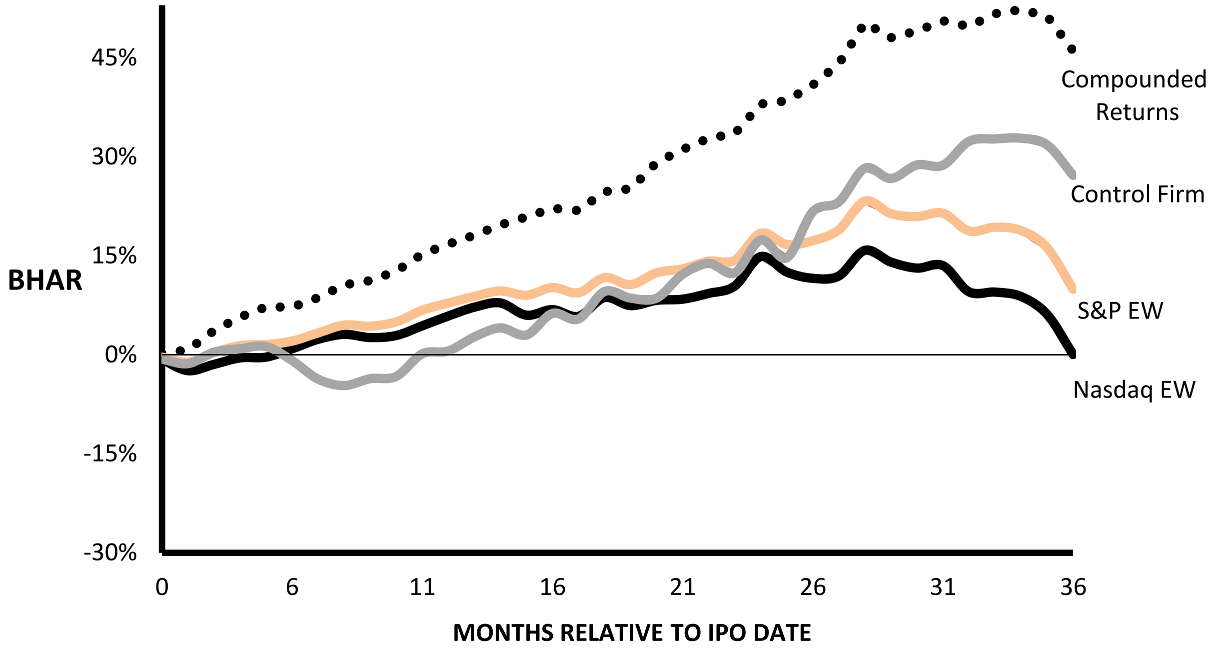
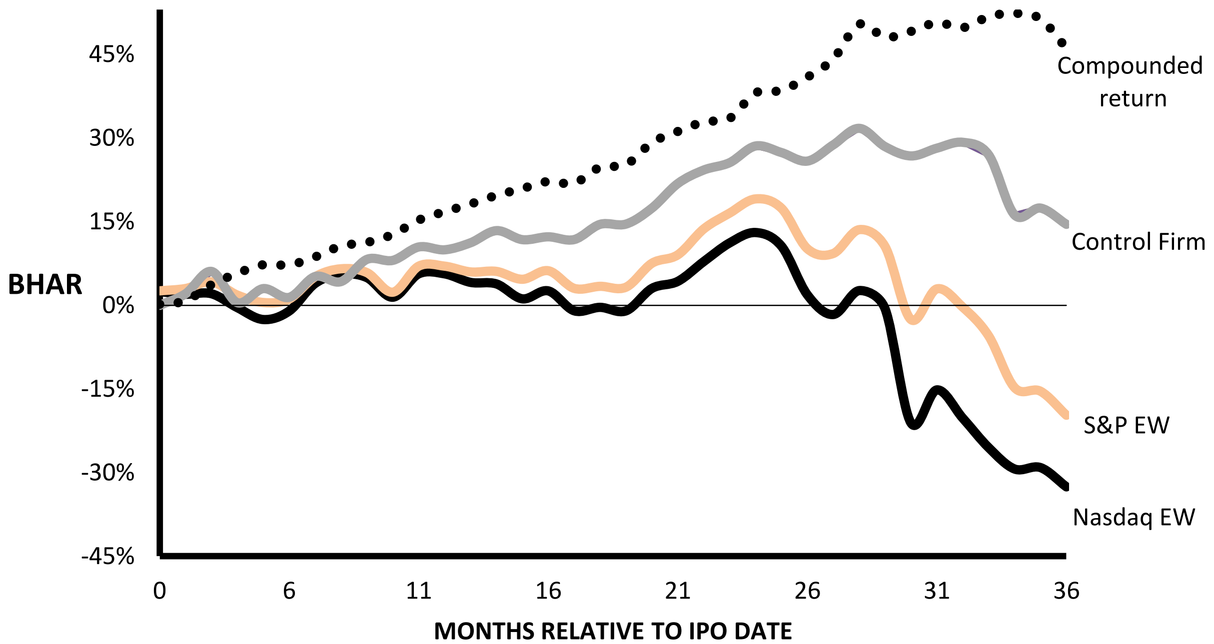


Figure 5 – Value-Weighted Buy-And-Hold Abnormal Returns for US Fintech industry

This plot presents the average Buy-And-Hold Abnormal Returns for a VW portfolio of the US fintech industry from 2005 to 2018. Four BHARs are observed: 1) Cumulative raw returns (no adjustment), 2) Control firm approach, 3) S&P 500 equal-weighted market index, and 4) Nasdaq equal-weighted market index. Month zero is the beginning of the return interval.



The usual t-statistic to test the presence of abnormal return was already presented. However, the literature suggests other tests, like non-parametric tests, while arguing that the t-statistic has little power in the event-time approach. Hence, Table 9 and Table 10 below present the Fisher´s sign test and the Wilcoxon sign-rank test, respectively, for CARs and BHARs.

Table 9 – Fisher´s Sign test

Fisher´s sign test is testing the null hypothesis that the sample median of abnormal returns is equal to zero. The test is calculated for CARs and BHARs, either for an equal-weighted or a value-weighted portfolio. The two benchmarks used are the Nasdaq Equal-Weighted market index and the control firm approach. This is a one-tailed test with the alternative hypothesis being the presence of positive abnormal returns. The p-values were introduced in the tables after conducting each test.

	EW		VW	
	Nasdaq	Control Firm	Nasdaq	Control Firm
BHAR	0.0000	0.0020	0.2025	0.0000
CAR	0.0015	0.2434	0.3986	0.2291

Table 10 – Wilcoxon Sign-rank test

Wilcoxon sign-rank test is testing the same null hypothesis as the Fisher´s test: an equal number of positive and negative abnormal returns. The test is calculated for CARs and BHARs, either for an equal-weighted or a value-weighted portfolio. The two benchmarks used are the Nasdaq Equal-Weighted market index and the control firm approach. This is a one-tailed test with the alternative hypothesis being the presence of positive abnormal returns. The p-values were introduced in the tables after conducting each test.

	EW		VW	
	Nasdaq	Control Firm	Nasdaq	Control Firm
BHAR	0.0000	0.0000	0.3705	0.0000
CAR	0.0845	0.2004	0.1499	0.1705

It is peculiar to notice that always for BHARs the null hypothesis testing that abnormal return is equal to zero is rejected with 1% significance level, excluding the case when the VW BHAR for the Nasdaq market index is used. This means that there is a strong evidence of positive performance for the US fintech industry. Contrarily, CARs present high p-values for almost all above scenarios. However, the Wilcoxon test for CARs reduces its p-values when compared to the sign test. This is due to the fact that Wilcoxon incorporates the size of the abnormal return.

In addition, Appendix H shows more evidence of positive performance of the fintech sector, when BHARs are computed using as a benchmark the CRSP cap-based portfolios.

It is not uncommon in past literature to face contradictory results in CARs and BHARs. In fact, it is extremely possible, as documented in Barber and Lyon (1997), since CARs are regarded as biased estimators of BHARs. As suggested by several scholars, CARs results are going to be disregarded for the final conclusions of this thesis.

5.2.2. Calendar-time results

After applying the event-time approach, literature firmly suggests computing also in a calendar-time framework. Therefore, two methods of this sort were calculated for the present purpose. First, in this section, the analysis of the results for the Fama-French three-factor model, and its extension, the Carhart four-factor model will be carried out. And last, the mean monthly calendar-time abnormal return and its main results will be addressed.

5.2.2.1. Fama-French Three-Factor Model and Carhart Four-Factor Model

Four regressions were performed to examine the presence of abnormal returns in a calendar-time fashion. Table 11 shows the values attained for all four regressions:

Table 11 – Fama-French Three-Factor and Carhart Four-Factor Models

Where $(R_{pi} - R_{bi})$ is the dependent variable, which is composed of the event portfolio return, R_{pi}, in excess of the 1 month Treasury-bill return, R_{bi}. The independent variables in this regression of which coefficients will be estimated are the following: $(RMRF_i)$ as the market portfolio; SMB_i as the difference in value-weighted return of small market cap and big market cap firms; and HML_i as the difference of value-weighted returns of high book-to-market and low book-to-market companies. Entries are the coefficients, and in parenthesis the t-statistics. The test performed is a two-tailed test statistic, which is computed for 90%, 95% and 99% confidence levels. Accordingly, one, two, or three asterisks refer to significance at 10%, 5%, and 1%, respectively.

	Full Sample EW	Full Sample VW	Full Sample EW	Full Sample VW
Intercept	0.3893	0.5299*	0.3794	0.51113*
	(0.93)	(1.76)	(0.91)	(1.7)
RMRF	0.9295***	0.9724***	0.9399***	0.9921***
	(8.14)	(11.85)	(8.51)	(12.47)
SMB	0.5570***	0.7589***	0.5557***	0.7563***
	(2.88)	(5.46)	(2.88)	(5.45)
HML	-0.4261**	-0.1511	-0.4020**	-0.1055
	(-2.35)	(-1.16)	(-2.38)	(-0.87)
MOM	-0.0386	(-0.0731)		
	(-0.37)	(-0.98)		
R^2	0.4088	0.6357	0.4083	0.6334

The first aspect that it is worth to emphasize about the estimation of these regressions is that introducing a momentum factor is quite irrelevant, as it can be verified looking to the inexistent change in R^2 when introducing the variable MOM, and also to the non-significance of the latter. Secondly, since the aim of this chapter is to better understand the behaviour of fintech stock after their IPO, it is relevant to check the significance and the sign of the intercept or the alpha, which in this regression represents the abnormal return. From Table 11, the sign of the intercept is always positive for all four regressions, meaning that the abnormal return is positive whether we use an equal-weighted or a value-weighted computation in our portfolio.

Regarding its significance, the value-weighted method yields at a 10% significance level that alpha is non-zero. Therefore, for a 95% confidence level, the alternative hypothesis that abnormal returns are positive is accepted. This contributes even further to the rejection of the so-called underperformance anomaly in IPOs as a specific phenomenon of this sort of corporate events and it points that fintech IPOs are performing better than the market on average. Although this is not a robust result in all possible methodologies.

Additionally, despite not being presented in the current dissertation, the FF Three-Factor was conducted with robust heteroskedastic standard errors in order to verify if heteroskedasticity had a great impact on the regression. However, given that the difference between both standard errors was marginally different, it is possible to infer that for this case heteroskedasticity is not present.

5.2.2.2. Mean Monthly Calendar-Time Abnormal Return

The last method to be discussed in order to provide further insights, particularly, in what concerns the existence of abnormal returns is the mean monthly calendar-time abnormal return. Table 12 displays the yearly calendar-time abnormal returns (YCTAR) for fintech IPOs. Moreover, a grand mean is computed for all YCTARs to gain an overall perspective of the CTAR approach.

From the table below, it is concluded that whenever abnormal returns are significant at least at a 10% significance level, it coincides always with the existence of positive abnormal return. This is once again supporting the idea of non-negative long-run performance obtained either using event-time BHARs or the calendar-time model Fama-French three-factor. At the end of the table, an average is done for all year calendar-time abnormal returns of this sample. For both benchmarks, regardless of whether an equal-weighting or value-weighting portfolio was used, a positive performance was the final outcome. When the control matching sample is computed to measure the abnormal return, this analysis reaches the conclusion that this sample presents positive performance in the long-run with a 97.5% confidence level.

Table 12 – Yearly Mean Calendar-Time Portfolio Abnormal Returns for US fintech IPOs.

Note that the YCTARs are computed for each month as the difference between the portfolio return and the benchmark return. Each month an equal or value-weighted portfolio is calculated considering all the companies with an IPO within the previous three years. The portfolio is monthly rebalanced and drops all companies that end the three year period or change their status into delisted. Entries are the coefficients, and in parenthesis the t-statistics. The test performed is a two-tailed test statistic, which is computed for 90%, 95%, and 99% confidence levels. Accordingly, one, two, or three asterisks refer to significance at 10%, 5%, and 1%, respectively. The benchmarks used are once again the Nasdaq EW market index and the control firm sample portfolio.

	Market		**Control Firm**	
Year	**VW**	**EW**	**VW**	**EW**
2005	1.33%	7.35%	0.26%	0.41%
	(0.6010)	(0.4527)	(0.0969)	(0.1837)
2006	3.66%***	2.14%**	4.92%**	3.46%**
	(3.4931)	(2.6495)	(2.3615)	(2.4508)
2007	2.45%**	1.66%*	2.53%*	2.61%**
	(2.3013)	(2.0683)	(2.0624)	(2.2706)
2008	0.52%	-1.28%	-3.03%	-5.56%*
	(0.23512)	(-1.0424)	(-0.9819)	(-1.8761)
2009	-1.98%	-1.46%	4.25%**	4.38%
	(-0.8111)	(-1.3457)	(2.3011)	(1.4651)
2010	-2.81%**	-0.72%	-0.30%	1.52%
	(-2.7170)	(-0.8792)	(-0.1604)	(0.8097)
2011	2.23%**	0.82%	1.49%	-0.13%
	(2.6199)	(1.5001)	(1.3303)	(-0.1023)
2012	-1.06%	-0.45%	6.67%	0.98%
	(-0.9508)	(-0.8081)	(0.5246)	(0.9204)
2013	0.52%	1.20%*	4.18%***	4.74%***
	(0.5050)	(2.0906)	(3.6051)	(4.5608)
2014	-0.42%	-1.00%	0.14%	-0.52%
	(-0.3616)	(-1.3054)	(0.0943)	(-0.3335)
2015	-1.71%	3.93%	-1.76%	0.22%
	(-0.7967)	(0.3341)	(-0.7617)	(0.1174)
2016	-0.91%	-0.01%	0.62%	1.16%
	(-0.9367)	(-0.0147)	(0.4194)	(0.6272)
2017	0.30%	-0.97%	2.51%***	1.01%
	(0.2692)	(-1.09731)	(4.4859)	(1.5021)
2018	0.73%	2.83%	0.96%	3.06%
	(2.8445)	(1.9813)	(0.2703)	(1.3772)
Grand mean (all periods)	**0.17%**	**1.27%**	**1.27%****	**1.14%****
	(0.4061)	(0.4905)	(2.4786)	(2.2024)

6. Limitations and Further Research

Even if several papers were conducted on the subject of IPOs underpricing and underperformance, I profoundly hope that the findings in this thesis contribute in a useful manner to develop future literature, in view of the fact that this thesis presents an unexplored industry set. For this reason, it would be beneficial to try to extend this analysis into a worldwide study of the fintech industry and analyse the main differences across countries and other industries. Also, it would be constructive to undertake a similar sort of investigation in the following years since this is a relatively new sector, and the long-run performance of a considerable number of young IPOs cannot be incorporated. Basically, the capacity of enlarging, even more, the size of the fintech set of companies would be clearly valuable, since the results would attain more power.

Other methodology could have been used to study the long-run performance in this thesis. Alongside with using a reference portfolio such as the Nasdaq market index and a control firm approach, a reference portfolio of similar firms sorted by size and book-to-market could have been constructed. Adopting a reference portfolio would allow identifying possible trends in firms' performance regarding the market size and other firm characteristics. It should be noticed, however, that the firm´s characteristics were taken into account when formulating the control firm method. Moreover, to achieve more robust results when computing the Fama-French three-factor model the factors could be constructed by purging IPOs. In other words, the factors should exclude firms that conducted an IPO in recent years.

7. Conclusions

In the following thesis, the study of two of the three major literature anomalies for initial public offerings was covered: underpricing regarding initial returns and underperformance in the long-run behaviour of stock for the US fintech industry. In this last chapter, the main findings are summarized and also the differences with existing literature are appropriately outlined.

7.1. Underpricing in the US Fintech

The primary phenomenon to be analysed delivers straightway conclusions in the above results: an equal-weighted mean initial return of 19.35% for the entire sample of US fintechs is registered from 2005 until the beginning of 2018. This is in accordance with a 14% initial return described by Ritter (2017), between 2001 and 2016. Although these results are not directly comparable, it seems that the fintech sector is attaining more initial returns on average, thereby, indicating the presence of systematic risk. Alternatively, if the signalling hypothesis is advocated, this would imply that fintech present higher quality compared to other sectors.

Additionally, three models were regressed on the level of underpricing to verify a set of hypothesis that previous literature elaborated on the ex-ante and ex-post uncertainty. In total, nine hypotheses were conducted in this procedure. In the end, exclusively for 3 variables the literature agrees on the results obtained. The variables are gross proceeds, a dummy concerning a venture-backed status and the underwriter reputation, although, for the latter, statistical significance is not achieved.

7.2. Long-Run Performance of US Fintech IPOs

In contrast with the short-run performance, results are no longer straightforward, and as affirmed by Kothari and Warner, this analysis is still quite “treacherous”. The results attained in the present thesis depend on the methodology selected. As previously affirmed, research on event studies does not agree on which methodology yields most accurate, well-specified, more robust and with higher power test statistics. In fact, scholars are split fundamentally into two groups: those who believe that anomalies are a real fact, and those that state that the market is not efficient, and anomalies are a real fact, and the other group that defends the market efficient hypothesis. Nonetheless, all agree that the choice of the methodology is relevant in determining robust inferences.

For this purpose, the CAR method and its results will be ignored, since its results are in clear contrast with all other methodologies applied. The first paper that identifies problematic issues regarding the cumulative event-time abnormal returns is Barber and Lyon (1997), where one of the problems being pointed out is that CARs are biased predictors of long-run BHARs. In this thesis, a negative biased is illustrated. This bias can be verified when comparing Figure 2 and Figure 3 (CARs) with Figure 4 and Figure 5 (BHARs).

When computing the BHAR approach, the outcome depends on which weights the portfolio was constructed on: under an equal-weighted computation, BHARs are strongly positive; if instead a value-weighted approach is followed to obtain the fintech portfolio, the latter is underperforming at the end of the third year only for the Nasdaq and S&P market index. However, if a control firm sample is applied as a benchmark, regardless of being an equal-weighted or a value-weighted portfolio, the fintech sector will show positive behaviour in the 3-year BHAR.

A Fisher´s sign test and a Wilcoxon sign-rank test was conducted to test the existence of positive abnormal returns. Only for the Nasdaq benchmark when using a value-weighted approach, BHARs do not show positive performance. These are the results when employing an event-time methodology.

Afterwards, the calendar-time approach was elaborated on two methods. Firstly, a multiple regression analysis was performed on Fama-French (FF) three-factor model, and also to the extension of the FF, the Carhart four-factor model. However, Ang and Zhang (2004) do not recommend using the Carhart approach because it creates model misspecification. This thesis reached the conclusion that adding one more factor to the model did not produce any substantial impact. Furthermore, equal-weight and value-weight portfolios achieve positive performance, although only for the latter statistical significance is presented.

Secondly, the yearly calendar-time abnormal returns (YCTAR) were computed for the Nasdaq and control firm as benchmarks. Statistical significance for negative abnormal returns across the years of the fintech sample was not verified in any year for both benchmarks and for both EW and VW approaches, while positive abnormal returns are recorded to be significant in 13 occasions.

In overall terms, the presence of the second anomaly known as “underperformance” is not verified. Instead, for the calendar-time approach and for event-time BHARs (with some exception, however) this study suggests even the presence of positive abnormal returns.

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9. Appendix

Appendix A: Table 1 - US Fintech Sample Overview

Table 1 - Overview of US Fintech companies with an IPO between 2005 and 2018

Company Common Name	IPO Date	Age	Lead Manager	Underwriter rep.	IPO Price	Close	Std Dev	Proceeds	Uses Proceeds	VC Backed
Amber Road Inc	21/03/2014	29.77	Stifel	Yes	13.00	17.00	0.04	96090345	6	Yes
Apigee Corp	24/04/2015	10.89	Morgan Stanley/ Cr	Yes	17.00	16.70	0.05	86955000	5	Yes
AppFolio Inc	26/06/2015	8.76	Morgan Stanley/ Cr	Yes	12.00	14.08	0.05	74400000	5	Yes
athenahealth Inc	20/09/2007	10.08	Bank of America-Me	No	18.00	35.50	0.03	113162742	5	Yes
Bankrate Inc	17/06/2011	35.01	Bank of America-Me	Yes	15.00	15.34	0.02	112500000	4	No
Bats Global Markets Inc	15/04/2016	10.83	Goldman Sachs	Yes	19.00	23.00	0.02	252700000	4	No
Black Knight Financial Services Inc	20/05/2015	7.93	Bank of America-Me	Yes	24.50	27.11	0.01	441000000	2	No
Blackhawk Network Holdings Inc	19/04/2013	11.84	Citigroup/ Deutsche	Yes	23.00	26.01	0.02	230000000	1	No
Blackline Inc	28/10/2016	15.37	Goldman Sach/ J.P.	Yes	17.00	23.70	0.04	146200000	5	No
Bofl Holding Inc	15/03/2005	104.75	The Seidler Compar	No	11.5	11.50	0.01	35100001	4	No
Borderfree Inc	21/03/2014	14.38	Credit Suisse/ RBC (	Yes	16.00	20.00	0.04	80000000	2	Yes
Cardlytics Inc	09/02/2018	9.62	Bank of America-Me	Yes	13.00	13.37	0.06	70200000	4	Yes
Cardtronics PLC	11/12/2007	18.49	Bank of America-Me	Yes	10.00	9.50	0.02	120000000	2	No
CaroliNA National Corp	15/12/2005	3.50	Scott and Stringfell	No	16.00	17.00	0.02	16000000	6	No
CBOE Global Markets Inc	15/06/2010	37.00	Goldman Sachs	Yes	29.00	32.18	0.03	339300000	3	No
CBOT Holdings Inc	19/10/2005	104.34	Credit Suisse First B	Yes	54.00	80.30	0.09	172340406	6	No
Change Healthcare Holdings Inc	12/08/2009	3.16	Morgan Stanley	Yes	15.50	16.52	0.02	356500000	1	No
ChannelAdvisor Corp	23/05/2013	11.93	Goldman Sach/ Stife	Yes	14.00	18.44	0.02	80500000	4	Yes
China Rapid Finance Ltd	28/04/2017	1.69	Credit Suisse/ Morg	Yes	6.00	6.40	0.05	60000000	5	Yes
Clayton Holdings LLC	24/03/2006	15.78	Piper Jaffray & Co/ \	No	17.00	21.00	0.03	127500000	2	No
Connecture Inc	12/12/2014	15.37	J.P. Morgan/ Morga	Yes	8.00	8.80	0.03	53080000	6	Yes
Cornerstone OnDemand Inc	17/03/2011	11.81	Barclays Capital Inc/	Yes	13.00	19.05	0.02	136500000	5	Yes
Cotiviti Holdings	26/05/2016	14.95	Goldman Sach/ J.P.	Yes	19.00	17.11	0.02	237500000	3	No
Coupa Software Inc	06/10/2016	10.64	Barclays Capital Inc/	Yes	18.00	33.28	0.04	133200000	6	Yes
Cowen Group Inc	13/07/2006	88.08	Cowen and Compar	Yes	16.00	15.88	0.02	179478272	2	No
CPI Card Group Inc	09/10/2015	8.35	BMO Capital Market	Yes	10.00	12.17	0.03	150000000	3	No
CURO Group Holdings Corp	07/12/2017	20.48	Credit Suisse/ Jeffe	Yes	14.00	14.20	0.01	93333338	3	No
Dealertrack Technologies Inc	13/12/2005	4.34	J.P. Morgan/ Lehma	Yes	17.00	19.25	0.01	170000000	2	Yes
Demandware Inc	15/03/2012	8.08	Deutsche Bank/ Gol	Yes	16.00	23.59	0.05	88000000	3	Yes
Dollar Financial Group Inc	28/01/2005	25.33	Jefferies/ Piper Jaff	No	16.00	16.00	0.02	120000000	3	Yes
eHealth Inc	13/10/2006	9.33	Bank of America-Me	Yes	14.00	22.90	0.03	70000000	6	No
Elevate Credit Inc	06/04/2017	3.18	Credit Suisse / Jeffe	Yes	6.50	7.76	0.03	80600000	3	Yes
Ellie Mae Inc	15/04/2011	13.83	Wells Fargo	No	6.00	6.77	0.03	45000000	7	Yes
Envestnet Inc	29/07/2010	11.12	Morgan Stanley/ UB	Yes	9.00	10.23	0.02	63000000	4	Yes
Epocrates Inc	02/02/2011	12.63	J.P. Morgan Securiti	Yes	16.00	21.96	0.05	85760000	3	Yes
Equity Bancshares Inc	11/11/2015	12.41	Keefe, Bruyette & V	No	22.5	23.89	0.01	43650000	5	Yes
EverBank Financial Corp	03/05/2012	7.88	Goldman Sach	Yes	10.00	10.60	0.02	192200000	3	No
Evertec Inc	12/04/2013	24.83	Goldman Sachs Co/	Yes	20.00	20.44	0.02	505263180	2	No
Fifth Street Asset Management Inc	30/10/2014	16.38	Morgan Stanley/ J.P	Yes	17.00	13.37	0.03	102000000	1	No
Financial Engines Inc	16/03/2010	13.75	Goldman Sach	Yes	12.00	17.25	0.03	127200000	4	Yes
First Data Corp	15/10/2015	26.52	Citigroup/ KKR Capi	Yes	16.00	15.75	0.02	2560000000	3	No
Five9 Inc	04/04/2014	12.30	Barclays Capital Inc/	Yes	7.00	7.64	0.03	70000000	7	Yes
Fleetcor Technologies Inc	15/12/2010	7.50	Goldman Sach/ J.P.	Yes	23.00	27.25	0.02	291525000	4	Yes
FX Alliance Inc	09/02/2012	5.38	Bank of America-Me	Yes	12.00	13.74	0.02	62400000	1	Yes
GAIN Capital Holdings Inc	15/12/2010	11.50	Morgan Stanley/ De	Yes	9.00	8.85	0.02	81000000	1	Yes
Genpact Ltd	02/08/2007	10.13	Citigroup/ J.P. Morg	Yes	14.00	16.75	0.03	494117652	6	No
GFI Group Inc	26/01/2005	17.61	Bank of America-Me	Yes	21.00	26.44	0.02	123001704	6	No
Global Brokerage Inc	02/12/2010	0.31	Citigroup/ Credit Su	Yes	14.00	14.85	0.02	210840000	3	No
Green Dot Corp	22/07/2010	10.74	J.P. Morgan/ Morga	Yes	36.00	43.99	0.02	164089800	1	Yes
Groupon Inc	04/11/2011	3.80	Morgan Stanley/ Go	Yes	20.00	26.11	0.07	700000000	1	Yes
Guidewire Software Inc	25/01/2012	10.35	J.P. Morgan/ Deutsc	Yes	13.00	17.12	0.03	115050000	5	Yes
Hamilton Lane Inc	01/03/2017	25.71	J.P. Morgan/ Morga	Yes	16.00	18.02	0.01	190000000	3	No
HealthEquity Inc	31/07/2014	11.87	J.P. Morgan/ Wells I	Yes	14.00	17.60	0.03	127400000	6	No
Heartland Payment Systems Inc	11/08/2005	8.16	Citigroup	Yes	18.00	24.51	0.03	121500000	5	Yes
Hexindai Inc	03/11/2017	3.38	Citigroup/ KKR Capi	No	10.00	12.66	0.05	1600000000	2	No
Higher One Holdings Inc	17/06/2010	10.01	Goldman Sachs	Yes	12.00	14.27	0.02	108000000	3	No
Inovalon Holdings Inc	12/02/2015	9.66	Citigroup/ Goldman	Yes	27.00	27.00	0.03	599999994	5	No
Interactive Brokers Group Inc	04/05/2007	29.89	HSBC/ WR Hambrec	No	30.01	31.30	0.03	1200400000	2	No
IntercontinentalExchange Inc	16/11/2005	8.42	Morgan Stanley/ Go	Yes	26.00	39.25	0.04	416000000	5	Yes

International Securities Exchange Holdings Inc	09/03/2005	4.73	Bear Stearns/ Morga	Yes	18.00	30.40	0.03	180887544	4	No
Intralinks Holdings Inc	06/08/2010	14.14	Credit Suisse/ Deut	Yes	13.00	13.00	0.02	143000000	2	Yes
J.G. Wentworth	08/11/2013	22.40	Barclays/ Credit Sui	Yes	14.00	12.82	0.02	136500000	2	No
Jianpu Technology Inc	16/11/2017	6.46	Goldman Sachs/ J.P	Yes	8.00	8.40	0.09	180000000	4	No
Leju Holdings Ltd	17/04/2014	5.84	Credit Suisse/ J.P. M	Yes	10.00	11.86	0.04	100000000	5	No
LendingClub Corp	11/12/2014	8.49	Goldman Sachs/ Mo	Yes	15.00	23.43	0.05	865500000	8	Yes
LexinFintech Holdings Ltd	21/12/2017	4.08	Bank of America-Me	Yes	9.00	10.70	0.10	108000000	8	Yes
LifeLock Inc	03/10/2012	7.48	Bank of America-Me	Yes	9.00	8.36	0.03	141300000	7	Yes
Liquid Holdings Group Inc	26/07/2013	5.11	Sandler O'Neill & Pa	No	9.00	7.64	0.05	28575000	5	No
Liquidity Services Inc	23/02/2006	6.27	Friedman Billings Ra	No	10.00	12.29	0.03	76873620	6	Yes
LPL Financial Holdings Inc	18/11/2010	42.43	Bank of America-Me	Yes	30.00	32.15	0.02	469724460	1	No
Markit Inc	19/06/2014	11.01	Barclays/ Bank of Am	Yes	24.00	26.70	0.01	1283336472	1	No
Mastercard Inc	25/05/2006	39.94	Goldman Sachs Co/	Yes	39.00	46.00	0.02	2399315568	4	No
Medidata Solutions Inc	25/06/2009	9.20	Citigroup/ Credit Su	Yes	14.00	17.00	0.02	88200000	6	Yes
Mindbody Inc	19/06/2015	17.01	Morgan Stanley/ Cre	Yes	14.00	11.56	0.04	100100000	6	No
Morningstar Inc	03/05/2005	20.96	W.R. Hambrecht	No	18.5	20.05	0.03	140831250	1	Yes
MSCI Inc	15/11/2007	38.42	Morgan Stanley	Yes	18.00	24.97	0.02	252000000	2	No
NantHealth Inc	02/06/2016	5.90	Jefferies/ Cowen an	No	14.00	18.59	0.04	91000000	1	Yes
National Commerce Corp	19/03/2015	8.76	Keefe Bryette & Wo	No	19.5	21.12	0.01	33150000	4	No
Nationstar Mortgage Holdings Inc	08/03/2012	17.73	Bank of America-Me	No	14.00	14.20	0.02	233333338	3	No
Netspend Holdings Inc	19/10/2010	11.34	Goldman Sachs/ Bar	Yes	11.00	13.00	0.03	203896473	5	No
NewStar Financial Inc	14/12/2006	2.50	Citigroup/ Goldman	Yes	17.00	17.71	0.03	204000000	3	Yes
Nymex Holdings Inc	17/11/2006	133.80	Bank of America-Me	Yes	59.00	132.99	0.03	383500000	7	No
On Deck Capital Inc	17/12/2014	7.51	Morgan Stanley/ Ba	Yes	20.00	27.98	0.04	200000000	5	Yes
OptionsXpress Holding Inc	27/01/2005	4.62	Bank of America-Me	Yes	16.50	20.30	0.02	198000000	5	No
PagSeguro Digital Ltd	24/01/2018	11.61	Goldman Sachs/ Mo	Yes	21.50	29.20	0.02	2265789433	3	No
Paycom Software Inc	15/04/2014	15.83	Barclays/ J.P. Morga	Yes	15.00	15.35	0.02	99675000	7	No
Paylocity Holding Corp	19/03/2014	16.76	Deutsche Bank	Yes	17.00	24.04	0.04	119765000	8	Yes
PayPal Holdings Inc	06/07/2015	16.56	Salomon Smith Barn	No	13.00	36.71	0.03	70200000	6	Yes
Penson Worldwide Inc	17/05/2006	10.92	J.P. Morgan/ Credit	Yes	17.00	19.50	0.02	126917937	6	Yes
PPDAI Group Inc	10/11/2017	5.40	Citigroup/ Credit Su	Yes	13.00	13.08	0.09	221000000	6	Yes
Premier Inc	26/09/2013	44.28	Bank of America-Me	Yes	27.00	30.65	0.01	760102866	2	Yes
Pros Holdings Inc	28/06/2007	22.04	Deutsche Bank/ J.P.	Yes	11.00	12.85	0.01	75075000	5	Yes
Q2 Holdings Inc	20/03/2014	8.97	J.P. Morgan/ Stifel	Yes	13.00	15.17	0.04	100891310	7	Yes
Qudian Inc	18/10/2017	3.34	China International	Yes	24.00	29.18	0.09	900000000	6	Yes
Redfin Corp	28/07/2017	13.12	Allen & Company/ C	Yes	15.00	21.70	0.07	138465000	3	Yes
Refco Inc	11/08/2005	36.16	Credit Suisse	Yes	22.00	27.48	0.02	583000000	6	No
RetailMeNot Inc	19/07/2013	5.84	Credit Suisse/ Gold	Yes	21.00	27.70	0.03	190909068	8	Yes
Riskmetrics Group LLC	25/01/2008	13.61	Credit Suisse/ Gold	Yes	17.5	23.75	0.03	245000000	1	Yes
Santander Consumer USA Holdings Inc	23/01/2014	18.61	Citigroup/ J.P. Morg	Yes	24.00	25.20	0.02	1799795280	1	No
SciQuest Inc	24/09/2010	15.28	Stifel Nicholaus	No	9.5	12.27	0.03	57000000	5	No
ServiceSource International Inc	25/03/2011	11.78	Deutsche Bank/ Mo	Yes	10.00	12.18	0.02	119401330	8	Yes
Shopify Inc	21/05/2015	10.65	Morgan Stanley/ Cre	Yes	17.00	25.68	0.05	130900000	8	Yes
Solera Holdings Inc	11/05/2007	40.91	Goldman Sachs/ J.P	Yes	16.00	18.40	0.02	420000000	4	No
Springleaf Finance Corp	16/10/2013	85.82	Bank of America-Me	Yes	17.00	19.26	0.02	357767516	1	No
SPS Commerce Inc	23/04/2010	22.86	Thomas Weisel Part	No	12.00	13.91	0.02	49160328	7	Yes
Square 1 Financial Inc	27/03/2014	8.78	Sandler O'Neill and	No	18.00	20.60	0.01	104060268	4	No
Square Inc	19/11/2015	6.42	Goldman Sachs/ J.P	Yes	9.00	13.07	0.02	243000000	5	Yes
SS&C Technologies Holdings Inc	31/03/2010	23.79	J.P. Morgan	Yes	15.00	7.54	0.02	160875000	5	No
Synchrony Financial	31/07/2014	10.89	Citigroup/ Goldman	Yes	23.00	23.00	0.01	2875000000	1	No
Tabula Rasa HealthCare Inc	29/09/2016	7.29	UBS/ Wells Fargo	Yes	12.00	14.88	0.04	51600000	8	Yes
TransUnion	25/06/2015	47.03	Bank of America-Me	Yes	22.50	25.40	0.01	664772737.5	1	No
TriNet Group Inc	27/03/2014	25.78	Deutsche Bank/ J.P.	Yes	16.00	19.10	0.04	240000000	1	No
Trulia LLC	20/09/2012	7.30	Deutsche Bank/ J.P.	Yes	17.00	24.00	0.03	102000000	4	Yes
Verifone Systems Inc	29/04/2005	23.87	J.P. Morgan/ Lehma	Yes	10.00	10.75	0.03	154000000	5	No
Verisk Analytics Inc	07/10/2009	38.31	Bank of America-Me	Yes	22.00	27.22	0.02	1875500000	1	No
Veritex Holdings Inc	09/10/2014	5.25	Sandler O'Neill and	No	13.00	13.95	0.03	35100000	3	No
Virtu Financial Inc	16/04/2015	6.84	Goldman Sachs/ J.P	Yes	19.00	22.18	0.02	314113168	6	No
Virtusa Corp	03/08/2007	11.13	J.P. Morgan	Yes	14.00	11.86	0.05	61600000	7	Yes
Visa Inc	19/03/2008	37.76	J.P. Morgan/ Goldm	Yes	44.00	56.50	0.04	17864000000	3	No
WageWorks Inc	10/05/2012	12.28	Credit Suisse/ Stifel	Yes	9.00	12.60	0.04	58500000	8	Yes

Appendix B: Control Firm Approach

To match firms on the basis of book-to-market and market value, we calculate the market value of a firm by multiplying the first closing price and the number of shares outstanding after the initial offering of equity. For book value of equity, we use COMPUSTAT and record the book value of equity right after the IPO as long it is within one year of the IPO date.

When choosing how to determine a set of control firms, the researcher usually faces a trade-off: or it gives more weight to the market value condition or instead of doing it so to the book-value criteria. Barber and Lyon (1997) recommend firstly filtering using 70-130% of market value to determine a set of control firms, and only after, picking the control firm with the closest book-to-market. However, in the following thesis, it was preferred to apply an initial symmetric condition of 50-150% to achieve a higher precision when selecting a control firm in terms of book value. Furthermore, the matching firm is screened in order to coincide with the time that our sample firm was listed.

Appendix C: Descriptive Statistics

Table 2 - Descriptive Statistics for US Fintech companies with an IPO between 2005 and 2018

Variable	Mean	Median	Std. Dev	Kurtosis	Skewness	Minimum	Maximum
Underpricing	0.200	0.163	0.279	9.964	2.119	-0.497	1.824
Age	18.820	11.554	23.711	14.949	3.613	0.311	156.560
Proceeds (M)	460.926	136.500	1632.881	103.544	9.758	16.000	17864.000
Revenues (M)	899.690	184.949	2301.355	31.252	5.155	2.328	18358.000
# uses of proceeds	4.117	4.000	2.143	-1.006	0.123	1.000	8.000
Offered/Out	0.399	0.256	0.327	-0.470	1.096	0.004	1.000
Market Cap (M)	2715.575	804.721	6892.243	39.495	5.872	41.264	56500.000
BtM	0.297	0.097	0.917	73.428	7.924	-0.295	9.249
TR Volume (M)	19.848	6.520	71.549	74.042	8.297	0.018	708.486

Appendix D: Statistical inferences

It is crucial to perform statistical tests when analyzing long-run abnormal returns. In this thesis, three tests are adopted for the results obtained when computing mean abnormal returns of the two event-time methods: CARs and BHARs. A parametric test (the conventional test statistic) and two non-parametric test (the Fisher´s Sign test and the Wilcoxon Sign-rank test) are elucidated below.

a) Conventional test statistic

When testing the null hypothesis that the mean cumulative or the buy-and-hold abnormal returns are zero, the following test statistic is executed for both cases:

$$\tau = \frac{\overline{CAR}_{1toT}}{\sigma(CAR_{1toT})/\sqrt{n}}$$

$$\tau = \frac{\overline{BHAR}_{1toT}}{\sigma(BHAR_{1toT})/\sqrt{n}}$$

Where $\overline{CAR}_{1toTt}$ and $\overline{BHAR}_{1toTt}$ are the average monthly abnormal returns, and $\sigma(CAR_{1toTt})$ and $\sigma(BHAR_{1toTt})$ are the cross-sectional standard deviations of abnormal returns for the portfolio of n companies.

b) Fisher´s Sign Test

In contrast to the test statistic, the Fisher´s sign test (Fisher, 1921) is testing the null hypothesis that the sample median of abnormal returns is equal to zero, instead of testing its mean to be equal to zero. This simple binomial test is concluded to be well-specified in Cohen (1992). For CARs and BHARs it is computed as:

$$S = \sum_{i=1}^{n} I(CAR_i > 0)$$

$$S = \sum_{i=1}^{n} I(BHAR_i > 0)$$

Where $I(CAR_i > 0)$ and $I(BHAR_i > 0)$ is equal to one every time that the long-run abnormal return is positive, and equal to zero in the opposite scenario. At a given significant level α, the null hypothesis is rejected for the case of a positive median when B ≥ b (α, n, 0.5). The constant b (α, n, 0.5) is the upper α percentile point of the binomial distribution with a probability of 0.5 of having one of the scenarios and n companies.

The common assumption for computing Fisher´s sign test is that abnormal returns are independent and follow the same continuous distribution. It is not required for calculating the sign test that the distribution should be symmetric. Ang and Zhang (2004) assert that the matching firm method with Fisher´s sign test shows the best performance.

c) Wilcoxon Sign-rank test

Introduced by Wilcoxon (1945), this test considers the sign of abnormal returns, as in the Fisher´s sign test, but also their magnitude. It bears in the null hypothesis the same hypothesis as the test before: the equal presence of positive and negative abnormal returns in the sample. In a simplified manner, it can be computed as follows:

$$WSR = \sum_{i=1}^{n} [I(CAR_i > 0)]R_i$$

$$WSR = \sum_{i=1}^{n} [I(BHAR_i > 0)]R_i$$

Where R_i is the rank of the abnormal return for firm i in absolute value. The Wilcoxon sign-rank consists of the rank of the abnormal return times its corresponding sign. Note that WSR is the sum of ranks with a positive sign, i.e. the ranks with a positive abnormal return.

When n is large enough, it can be demonstrated that test statistics will converge to a normal distribution. The null distribution of WRS will be such as:

$$WSR \sim N(E(WSR), \sigma^2(WSR))$$

$$E(WSR) = n(n+1)/4$$

$$\sigma^2(WSR) = n(n+1)(2n+1)/24$$

Appendix E: Description of independent variables for regressions on initial returns

Variable	Description
Ln(Age)	Logarithm of difference between the foundation date and the IPO date proceeds of the IPO.
2014+ Dummy	Dummy variable that gives 1 whenever an IPO occurred after January 2014, and 0 otherwise.
Underwriter reputation	Dummy variable that gives 1 for underwriters considered with high prestige, and 0 otherwise.
Std Dev 20 returns after IPO	Standard deviation of the first 20 trading days after IPO.
Ln(Proceeds)	Logarithm of total proceeds of the IPO.
# of uses of proceeds	The number of uses of proceeds described in the firm´s prospectus.
Venture-backed	Dummy variables that delivers 1 every time a company is venture-backed, and 0 otherwise.
Ownership Retention	Number of shares offered.
TR Volume	Number of shares trading at the IPO date.
Ln(Market Cap)	Logarithm of the firm value.
ln(Revenues)	Logarithm of company revenues.

Appendix F: Underpricing level for US Fintech sector

Table 3 - Overall level of underpricing for the entire sample

Mean 1st Day Return	Total Nº of IPOs	t-stat
19.35%***	128	7.8109

*: Statistically significant on 10% significance level
**: Statistically significant on 5% significance level
***: Statistically significant on 1% significance level

Table 4 - Initial Return, Volume and t-stat by cohort year

Year	1st Day Return	Nº IPOs	t-stat
2005	21.46%***	14	3.5414
2006	30.16%*	9	2.2268
2007	20.88%	8	1.6845
2008	14.20%	2	1.0000
2009	17.24%*	3	3.2093
2010	8.85%	14	1.6152
2011	15.28%	7	1.3418
2012	27.66%**	9	3.1892
2013	15.72%*	9	2.0702
2014	17.04%***	19	4.2954
2015	21.67%	15	1.7385
2016	27.45%*	7	2.3619
2017	15.74%***	10	3.6741
2018	19.33%	2	1.1727

*: Statistically significant on 10% significance level
**: Statistically significant on 5% significance level
***: Statistically significant on 1% significance level

Appendix G: Addressing multicollinearity and heteroskedasticity

1. Test for Multicollinearity

The variance inflation factor (VIF) test indicates the size of an upward inflation impact on standard errors. The following test was conducted for all three underpricing regressions.

MODEL 1

Variable	VIF
Ln(Proceeds)	3.32
Ln(MarketCap)	3.17
Trade Volume	2.46
Ln(Revenues)	1.63
Std dev (first 20 days)	1.15
Mean VIF	2.34

MODEL 2

Variable	VIF
Ln(Proceeds)	5.47
Ln(MarketCap)	4.37
Trade Volume	2.9
Ln(Revenues)	1.82
Ownership Retention	1.58
Std dev (first 20 days)	1.56
# Uses of Proceeds	1.45
Venture-Backed	1.39
Underwriter reputation	1.28
Mean VIF	2.42

MODEL 3

Variable	VIF
Ln(Proceeds)	5.62
Ln(MarketCap)	4.6
Trade Volume	3.06
Ln(Revenues)	1.84
Ownership Retention	1.71
Std dev (first 20 days)	1.57
Venture-Backed	1.46
# Uses of Proceeds	1.45
Underwriter reputation	1.3
Ln(Age)	1.29
2014+ dummy	1.22
Mean VIF	2.29

2. Correlation matrix for all independent variables

The following matrix shows the correlation coefficients of all explanatory variables. The diagonal of the matrix is a set of 1 because it represents the correlation between a variable and itself.

	Ln(Age)	2014+ Dummy	Underwriter reputation	td Dev 20 returns after IP	Ln(Proceeds)	# of uses of proceeds	Venture backed
Ln(Age)	1						
2014+ Dummy	-0.2044	1					
Underwriter reputation	-0.0158	0.0629	1				
Std Dev 20 returns	-0.2423	0.2546	0.0916	1			
Ln(Proceeds)	0.2259	-0.0092	0.2804	-0.0816	1		
# of uses of proceeds	-0.1549	0.1247	0.0448	0.3422	-0.3684	1	
Venture backed	-0.2893	0.0104	0.0872	0.297	-0.3347	0.313	1
Ownership Retention	-0.1569	0.1856	0.0813	0.1706	0.3058	-0.0842	-0.1197
TR Volume	0.2791	-0.0406	0.4021	-0.0249	0.7406	-0.1184	-0.1213
Ln(Market Cap)	0.1916	0.1228	0.2089	0.1633	0.758	-0.1351	-0.1404
ln(Revenues)	0.2025	0.1198	0.1216	-0.0632	0.5775	-0.2969	-0.3514

3. OLS regression with White standard errors of OLS

The purpose of this regression is to verify how problematic can be the existence of heteroskedasticity for the regressions conducted. Nevertheless, although test statistics are indeed lower, it can be concluded that individual significance of each variable does not change substantially.

Table 6 - Model 3 with Robust Heteroskedastic Standard Errors

A sample of 128 fintech companies is used for these regressions. The first trading day return is the independent variable (calculated as the percentage change of the first-day closing price from the offer price). Entries are the coefficients, and in parenthesis the t-statistics. The test performed is a two-tailed test statistic, which is computed for 90%, 95% and 99% confidence levels. Accordingly, one, two, or three asterisks refer to significance at 10%, 5%, and 1%, respectively.

Variable	Model 3
Intercept	-1.23***
	(-2.74)
Std dev (first 20 days)	-2.63*
	(-1.66)
Ln(Proceeds)	-0.12**
	(-1.81)
Trade Volume	-0.04
	(-1.43)
Ln(MarketCap)	0.22***
	-3.40
Ln(Revenues)	-0.02
	(-0.97)
Underwriter reputation	0.03
	(-0.49)
# Uses of Proceeds	0.02
	(-1.41)
Venture-Backed	0.13**
	(2.25)
Ownership Retention	(-0.07)
	(-0.92)
Ln(Age)	0.02
	(-0.56)
2014+ dummy	-0.06
	(-1.43)

Appendix H: More evidence on BHARs

Figure 6 - Equal-Weighted Buy-And-Hold Abnormal Returns for US Fintech IPOs
This plot presents the average Buy-And-Hold Abnormal Returns for an EW portfolio of the US fintech industry from 2005 to 2017 using CRSP cap-based portfolios. Three BHARs are observed: 1) "Large firm" [CRSP cap-based 1st Decile Portfolio for Nasdaq Stock Market], 2)" Medium firm" [CRSP cap-based 5th Decile Portfolio for Nasdaq Stock Market], and 3) Small firm [CRSP cap-based 10th Decile Portfolio for Nasdaq Stock Market].

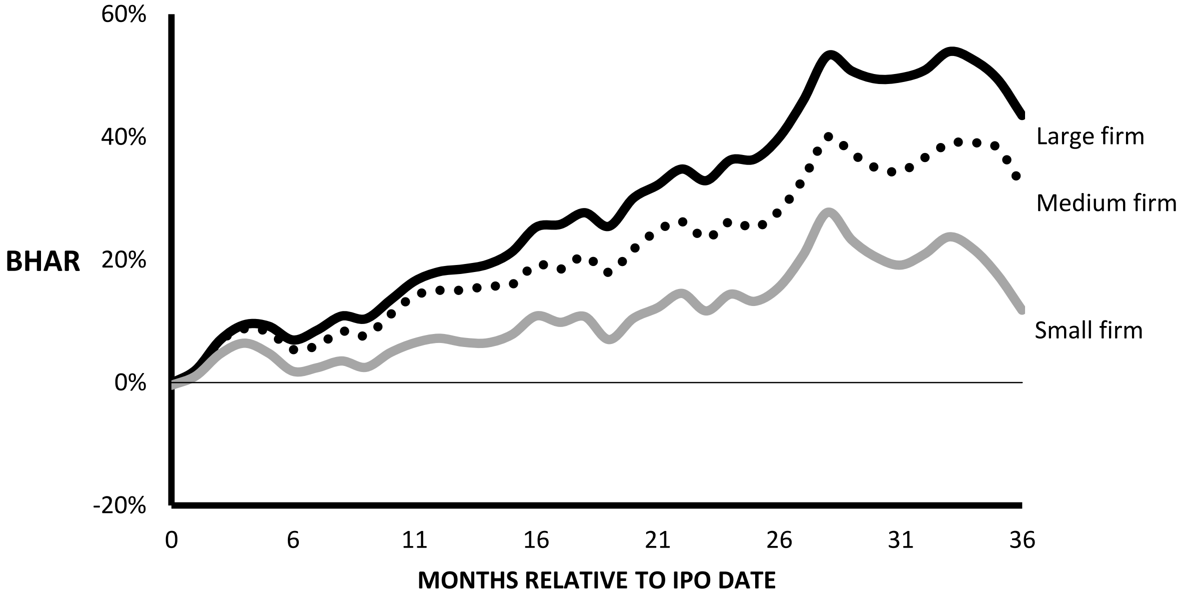

Figure 7 -Value-Weighted Buy-And-Hold Abnormal Returns for US Fintech IPOs
This plot presents the average Buy-And-Hold Abnormal Returns for a VW portfolio of the US fintech industry from 2005 to 2017 using CRSP cap-based portfolios. Three BHARs are observed: 1) "Large firm" [CRSP cap-based 1st Decile Portfolio for Nasdaq Stock Market], 2)" Medium firm" [CRSP cap-based 5th Decile Portfolio for Nasdaq Stock Market], and 3) Small firm [CRSP cap-based 10th Decile Portfolio for Nasdaq Stock Market].