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The IPO Performance of FinTech Companies

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PREFACE AND ACKNOWLEDGEMENTS

Writing this thesis was a process of constant improvements, perseverance and hard work. I am satisfied that I choose to analyze FinTech companies, as there hasn't been a lot of research on the FinTech IPO performance. Therefore, I hope that this thesis provides (new) insights in the post-IPO performance of FinTech companies, which are in an innovative and fast-growing sector.

I would like to thank my friends and fellow college mates for all the fun and help during my time at the Erasmus University.

And off course, I would like to thank my family, especially my parents, who were the greatest support and made it able for me to study at this university.

ABSTRACT

This master thesis examines the stock performance of 96 North-American (US and Canadian) and 41 European FinTech companies, with an initial public offering between 2005-2017. For the short-term performance, significant underpricing-levels of 17% for North-American and 10% for European FinTech companies are found. The North-American FinTech companies are significantly more underpriced than the European FinTech companies. From the regressions appear that venture backed capital and firm age have a significant effect on the underpricing. For the long-term, the three-year buy-and-hold abnormal return (BHAR) appears to be positive, which is in strong contrast with prior findings of long-term IPO performance.

Keywords: FinTech, IPO, Underpricing.

JEL Classification: G24, G32

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CHAPTER 1 Introduction

1.1 General

"Early investor calls LendingClub IPO 'no-brainer'", (Greene, 2014). On 11 December 2014 was the initial public offering (IPO) of LendingClub, on the New York Stock Exchange. The shares of the company were initially priced at $15. After an hour, the shares were already trading at a price of $24.75, implying a 65% markup on the opening price. Some investors on the trading floor were surprised that the company 'had left so much money on the table' (Alloway, Platt, & Waters, 2014). At the end of the day the stock price closed at $23.43, implying an underpricing of 56.2%.

LendingClub Corporation is a so called financial technology (FinTech) company. FinTech companies, or FinTechs, are companies using technology to make their financial services more effective and efficient (McKinsey, 2016). FinTech nowadays is often said to represent innovation in the financial services sector, which either can be the new products of startups or the adoption of new methods by existing companies, where technology is leading (KPMG, 2016). There are different areas (key verticals) within the FinTech sector: Lending tech, Payments/billing tech, Personal finance/wealth management, money transfer/remittance, Blockchain/bitcoin, Institutional/capital markets tech, Equity crowdfunding, InsurTech (KPMG & CB Insights, 2016).

The financial services industry is expected to be the next industry, after the retail and media industry, which changes by software-enabled innovation (Soule, 2016). A large part of the industry has acknowledged the change of the industry and is investing in FinTech. According to the quarterly published 'the pulse of FinTech' report of KPMG and CB Insights, the global investments in FinTech accounted $3.2 billion in the first quarter of 2017. Substantial amounts of $1.5 billion in US FinTechs and $880 million in European FinTechs was invested. Obviously, the investments in US and European FinTechs are a substantial part of the total global amount of invested money. According to Dealogic 111 firms went public on US stock exchanges in 2016, thereby raising $24 billion of capital (The Wall Street Journal, 2017), $1,014 billion of that total amount was raised by seven FinTech companies (Financial Technology Partners, 2017).

In general, the overall reasons for firms to go public is to raise equity capital and to provide more liquidity for its current shareholders, by giving them the opportunity to sell their shares on a public market (Ritter & Welch, 2002). An underwriter, which is usually an investment bank, helps the firm with the IPO process, but for many years there appear to be 'anomalies' regarding the short- and long-term performance of the shares after the IPO. Underpricing is one of the most common known anomalies, which is defined by the average returns made by investors on the first trading day. Another anomaly with IPOs is the long-term underperformance of an IPO, measured over a one-year or a three-year period.

1.2 Aim Thesis

The IPO performance of companies has been researched extensively, usually the researched is not restricted to a certain sector or industry. Besides, the financial services industry is constantly changing and challenged by the growing role of FinTech. And the number of FinTechs and the investments in FinTech are substantially growing. Because FinTech is a relatively new, although, continuously growing, (part of the) financial services sector, there hasn't been done much research on these companies yet. The purpose of this thesis is to provide new insights into the IPO performance of FinTech companies, by examining the post-IPO short-term (underpricing) and long-term stock performance. The research question of this thesis therefore is:

What is the short- and long-term IPO performance of European and North-American (US and Canadian) FinTech companies?

Prior research provides evidence for the existence of underpricing on the stock markets, for instance Loughran and Ritter (2004), who examined the existence of underpricing in the United States for several periods, find average first-day returns of 7% during 1980-1989, around 15% during 1990-1998 and 12% for the period of 2001-2003, for the US stock markets. Also for the main markets in Europe evidence of underpricing has been found. Derrien and Womack (2003) find an average underpricing of 13.23% for the period 1992-1998 in France. Where Ljungqvist and Wilhelm (2002) examined the period of 1990 – May 2000, and find an average underpricing of 16.5% for France and 40.2% for Germany. Evidence for the long-term underperformance of IPOs is also provided by previous research. Ritter (1994) found for IPOs in the US (1975-1984) that the return of the first three years after the IPO was at an average of 27% lower, than the returns of comparable listed companies (van der Sar, 2015). It appears that there are factors which could possibly influence underpricing. The effect of these factors has been examined, Clarkson and Merkley (1994) for instance find that firms with larger gross proceeds have a smaller level of underpricing, and Mauer and Senbet (1992) find a negative relation between underpricing and company age.

According to Ritter (1991) there are several reasons why the long-term underperformance is an interesting anomaly, among others the long-term underperformance can lead to doubts about the information efficiency on the IPO offering markets, and the existence of price patterns can reflect opportunities for trading strategies with positive abnormal returns (Ritter, 1991). Evidence for the long-term underperformance of IPOs is provided by several researchers. Ritter (1994) found that the three-year return on the aftermarket amounted 27% less than that of comparable firms, during the period 1975-1984. And for the period 1970-1990, Loughran and Ritter (1995) even find an underperformance of 51%, over a five-year period on the aftermarket.

The thesis will aim at IPOs of North-American (defined as US and Canadian) and European companies with an IPO between 2005 and 2017. This specific period is selected, because of the likeliness that in this period most (modern) FinTech companies went public. Because of the geographical difference, there is the possibility to compare the IPO performance of the North-American companies with the performance of the European companies. Over time, some firms are acquired by others, therefore when examining the short-term performance, the number of observations is larger than for the long-term performance. The dataset for underpricing consists of 96 US and Canadian firms and 41 European firms. For analyzing the long-term performance, the number of firms declines in comparison with the short-term performance, due to the date of the IPO.

The short-term performance is measured with the average first-day returns, where the existence of positive average first-day returns indicates (the degree of) underpricing. Furthermore, several factors of ex-ante uncertainty will be regressed on the underpricing. Along this way, it is possible to conclude which factors can (partly) explain the underpricing of the FinTechs. The long-term performance is measured on a one-year and three-year period, and is calculated with buy-and-hold abnormal returns, following the methodology of Ikenberry, Lakonishok and Vermaelen (1995), also the (cumulative) average abnormal returns are calculated, following the method of Ritter (1991). From the results of both the short- and long-term performance can be deduced how the stocks of FinTech companies perform after the IPO. Because the results are reported separately for the North-American and European firms, a comparison between the results of both regions can be made, which will lead to several differences on the short- and long-term performance.

1.3 Main results

Regarding the short-term performance, several levels of underpricing are found, for North-American FinTechs 17%, for European FinTechs 10%, and for both combined 15%. It appears that firm age, firm size (market capitalization), proceeds and venture backed firms have a significant effect on the underpricing. For the long-term performance, North-American FinTechs have an average buy-and-hold abnormal return (BHAR) of 4.31% on a one-year period, and a BHAR of 14.31% on a three-year period, the European FinTechs have a BHAR of -23.36% and 0.16% on a one-year and three-year period, respectively. When the companies of both regions are combined a one-year BHAR of -4.07%, and a three-year BHAR of 10.15% is found.

1.4 Set up Thesis

The structure of this thesis is as follows, section 2 called ‘The FinTech Landscape’ will elaborate on the FinTech industry, including the history of FinTech, the FinTech investment climate and the different sectors, also called verticals. Sections 3.1 Short-term performance and 3.2 Long-term performance discuss underlying theories, explanations and prior research. Furthermore, along with the theories and past empirical results from prior research, which are used to form hypotheses. Then, section 4 Data discusses the data. Forming a dataset of European and US and Canadian FinTech companies, is a time-consuming part, the steps of constructing this dataset are elaborated in this section. After describing how the dataset is constructed, the descriptive statistics of the European and North-American FinTechs are discussed. Section 5 Methodology, discusses the used methods for analyzing the short-term and long-term performance. First, section 5.1 describes the regressions used on the underpricing, section 5.2 outlines the methodology of the (cumulative) abnormal returns following Ritter (1991), and third, section 5.3, discusses the methodology on the buy-and-hold abnormal returns following the paper of Ikenberry, Lakonishok and Vermaelen (1995). Thereafter, section 6 presents the results. First, the results of the short-term performance, which are the levels of underpricing for Europe and North-America, followed by the regression results, and second, the results of the long-term performance, showing the average buy-and-hold abnormal returns and the average firm adjusted abnormal returns. As last, section 7 provides the conclusions and the limitations of this thesis, and recommendations for further research.

CHAPTER 2 The FinTech Landscape

Worldwide the largest retail banks are still the dominating players in the financial services industry, offering deposit, payment and credit services that are used daily by everyone, but already for some years they are not the only players in this industry anymore. For example, when shopping online one can choose to pay with a debit card, but also companies like PayPal and Afterpay provide payment solutions. Regular credit customers of banks, businesses as well as individuals, can now chose for peer-to-peer (P2P) platforms or specialist lenders for loans. Accessibility and convenience are the assumed to be the largest advantages. Alternative finance is increasingly winning popularity among customers, therefore FinTech is coming closer and closer to its breakthrough point, which is the moment that a significant amount of (business) customers will recognize the solutions, driven by technology, as a profitable and, even more, a better option than the services provided by the large institutions (Barberis & Chishti, 2016).

2.1 FinTech definition

The term ‘FinTech’ originates from the early 1990s, where it would refer to a project called ‘Financial Services Technology Consortium’, started by Citigroup to boost technological cooperation effort (Arner, Barberis, & Buckley, 2015). However, since 2014, regulators, consumers and market participants have increased their focus of attention for this sector (Arner, Barberis, & Buckley, 2015). The rapid growth of FinTech caused greater regulatory scrutiny, which could be justified by the important role of FinTech in the financial sector.

Currently FinTech is mostly seen as a combination of financial services with information technology (IT). But finance and technology were already linked for a long time. Important reason for FinTech now evolving, is The Global Financial Crises of 2008, which caused a loss of confidence in the traditional financial companies, resulting in opportunities for startups in this sector. This is constantly posing challenges for regulators and market participants, especially to keep a healthy balance between the possible benefits of innovation and the possible risks. Private Equity firms, Corporates, VC firms and several other investors have invested enormous sums of money in FinTech startups after the crisis. Reflected by the total amount of 50 billion dollars invested in about 2500 firms since 2010 (Accenture, 2016).

Gulamhuseinwala, Bull, & Lewis (2015) define FinTech companies as connectors of innovative business models and technology, which the intention to enable, enhance and disrupt the financial services sector. On the other hand, Arner, Barberis and Buckley (2015) state that FinTech as a concept is not restricted to certain sectors or business models (such as alternative payments solutions), but that it includes the whole area of products and services which are originally provided by the financial services sector.

According to the first of the, quarterly published, ‘The Pulse of FinTech report’ of KPMG (2016), FinTech covers a various area of firms, business models and technologies, but in general firms can be placed into several categories of FinTech, also called key verticals, which are: Lending tech, Payments/billing tech, Personal finance/wealth management, Money transfer/remittance, Blockchain/bitcoin, Institutional/capital market tech, Equity crowdfunding, InsurTech (KPMG, 2016). In the next section, the different verticals will be elaborated in section 2.3 The FinTech verticals.

2.1.1 The history of the FinTech evolution

In 1967, the Automated Teller Machine (ATM) was launched, which was the start of a modern period of financial technology. In the period 1967-1987 financial services industry changed from an analogue to a digital industry (Arner, Barberis, & Buckley, 2015). In this period, financial institutions started increasingly using IT in their internal operations.

Another FinTech development period can be marked from 1987 (up till 2008). Late in the 1980s, the financial services industry had mostly turned into a digital industry, based on the electronic transactions between financial companies, mutually, and customers. With the rise of the internet, around 2000, a new level of development was initiated. Around 2001, eight US banks had more than one million online customers. And in 2005 the first banks without customer offices emerged in the United Kingdom. In the early 2000s also a lot of activities of banks became digitalized, which was reflected in the significant spending on IT by the financial services industry. Also, market regulators, particularly security exchanges, kept increasingly using technology.

According to Arner, Barbaris and Buckley (2015) the Global Financial Crises marks a turning point in the history of FinTech development. The crisis has been an accelerator for the growth of a new FinTech period (2009-now). The market conditions changed, thereby providing opportunities for new innovative companies to establish on the market. This resulted in an explosive increase in the number of new, led by technology, financial services entrants, in the last few years (Gulamhuseinwala, Bull, & Lewis, 2015).

FinTech has known several evolutions in time, and of course the FinTech sector will undergo new evolutions in the future. Since the focus by regulators, consumers and market participants on the FinTech sector has been sharpened only since 2014, it is a logical consequence that there hasn’t been done a lot of research on the (stock) performance of the companies in this sector yet. Which is due to several factors, first, the evolution of FinTech over time, the sector is definitely not the same as ten years ago, and second, the attention, also for research, is explosively increased only since a few years. Besides, IPO researches usually do not focus on one specific sector, which is the case in this thesis.

FinTech sector has been evolving during and after the Global Financial Crisis, which makes it interesting to see the IPO performance of firms before and after the crisis. Investors, companies, market participants and even regulators can benefit from the findings of research, as it will touch some of their working fields in a certain way. For instance, innovative startups are always an attractive (investment) target for competitors and/or investors, but on the other hand, are also interesting to bring to the stock market, for the founders of the companies. Besides, in the (near) future perhaps an increasing number of FinTech firms will perform an IPO. As in case of the IPO of LendingClub, where the underpricing was high, the founders, investors and LendingClub itself, could have had more proceeds if they knew what factors were affecting the level of underpricing of FinTech companies. The factors affecting the underpricing of FinTech companies, can be different from the factors affecting the underpricing of companies of other sectors, which are usually examined in general, instead of on a specific sector. This thesis will not only examine companies with an IPO after the crisis, but also those before the crisis, up till 2005. Consequently, an overview of the IPO performance of (a large part of) the FinTech sector of the last 12 years is provided.

2.1.2 Advantages of FinTech

'The FinTech wave', of rapid emerging startups and opportunities, has corresponding features with all other 'waves' of disruptive innovations, however it also has some characteristics that are specific to the finance industry (Phillippon, 2016). Most important advantage of startups is that they are prepared to take risks and are not limited by the current system(s). Other important advantages of FinTech are the highly standardized and low-cost financial services, reliance on internet, so less need for geographical concentration, change in behavior of consumers, (currently) less regulation of financial services, relatively lower exposure to risk by the services and products (Romãnova & Kudinska, 2016).

2.2 The FinTech (booming investment) climate

The $50 billion invested in about 2500 FinTech firms since 2010, reflects the huge attraction of the FinTech sector on investors. Most popular firms are online lenders, payment providers, cryptocurrency companies, and providers of personal wealth management (Crosman, 2015). FinTech is currently one of the hottest sectors in venture capital. The general view of the FinTech situation by bankers, investors and analysts has slightly changed from seeing a bubble, to seeing a healthy, but hot, investment situation (Crosman, 2015). This is caused by a few companies, which proved their value, leading to satisfied investors, for example LendingClub's IPO of $1 billion. But the constantly growing number of startups and investors is putting lots of pressure on the sector.

The first accelerators of the 'post-crisis FinTech' growth were some entrepreneurs, establishing companies with innovative retail financial service solutions (Crosman, 2015). This has put lot of attention on the FinTech sectors, which was strengthened by the effect of the financial crisis, drawing a negative image of banks and traditional financial service companies. The venture capital firms rapidly chased the entrepreneurs into FinTech.

FinTech is not the only hot sector for venture capital, as venture capital is, at this moment, overall hot, driven by the presence of a bull market and the low interest rates. However, in perspective, the investments are not, yet, comparable with the investments in technology at the end of the 1990s, in the dotcom bubble. Another difference is that there is more fundamental information available, which enables it to do better valuations. Overall, men cannot speak of a FinTech bubble in the current situation, but that the sector is hot is an understatement (Crosman, 2015). And as in every hot sector, there will be big winners and big losers.

According to Anand Sanwal, CEO and co-founder of CB Insights (which also writes reports on FinTech), the current investment rate in FinTech will not hold in the long run, because the current growth of investments is so peculiarly high, that the increasing growth of investments will not hold in the future. It appears that the financing climate is very well, but there have been relatively few exits yet, so the exit climate appears to be not good (Crosman, 2015). IPO research on the FinTech companies, will also provide insights in the performance of past exits.

2.3 The FinTech verticals

2.3.1 Lending tech (alternative lending)

FinTech companies falling into the category Lending tech, are primarily (online) peer-to-peer lending (P2P) platforms and underwriter- and lending platforms that make use of machine learning technologies and algorithms to estimate the solvency of customers (KPMG & CB Insights, 2016). Lending tech or alternative lending typically aims at businesses and individual borrowers, which are, most of time, not able to get a loan at traditional finance institutes. Alternative lending is often supported by digital data and most of the loans are unsecured or backed with alternative collaterals (Aveni, 2015).

Moreover, P2P lending can be described as classical financial services, namely providing of consumer loans, but offered on a technological platform (usually online platforms). Lending Tech is backed by technology, innovation and disruption, and has a potential impact on millions of people because of its accessibility. Lending tech is a general term for the whole scale of online lending providers. Firms differ from commercial to social (non-profit), some facilitate direct lending online, where others have partnerships with traditional lending companies. Examples of direct online lending companies are LendingClub (P2P) and OnDeck Capital. Another company, LendingTree, is a connector (or broker) and brings potential borrowers and banks, lenders and credit partners, together.

2.3.2 Payments/billing tech

Payment and billing tech companies are companies that provide solutions varying from facilitating payments processing to payment card developers to subscription billing software tools (KPMG & CB Insights, 2016). According to Kim et al. (2016), the rapid growth of the mobile payments market, led by convenient payment services, is the fastest growing vertical of the FinTech sector.

The payment vertical has a large variety of payment instruments and activities at different stages of the payment process (Jun & Yeo, 2016). Before being able to provide payment services to consumers, the platform must go through all stages of the payment process. Contrarily, because of the structure of several tiers, the platform is not required to own all the necessary facilities and licenses itself, to be able to provide payment services. The platforms can enter and use the facilities of another (rival or partner) platform (Jun & Yeo, 2016). Given the stages of the payment chain, the kind of service, and the predominant types of relationships with banks, it is possible to classify non-financial payment service providers in four separate categories, namely, front-end providers, back-end providers, operators of retail payment infrastructure, and end-to-end providers (Jun & Yeo, 2016).

Front-end providers, for instance ApplePay and iDeal, offer front-end services, including authorization, pre-transaction and post-transaction. These front-end services generally are depending on back-end services, which are provided by other companies, which can be (rival) end-to-end providers in the market. End-to-end providers are banks, credit card companies (e.g. Visa and MasterCard), or other payment platforms like AfterPay and PayPal. These companies are able to provide front-end services and back-end services, among which are functions of the clearing and settlement process (Jun & Yeo, 2016).

2.3.3 Personal finance/wealth management (WealthTech)

Tech companies provide solutions to individuals to manage their bills, (bank) accounts, credit and their personal assets and investments (KPMG & CB Insights, 2016). WealthTech aims on improving and transforming wealth management and investments, by focusing on the inefficiencies in wealth management (Financial Technology Partners, 2017). The benefits come from more efficient workflows, more optimal portfolio management, more access to assets, better customer experiences and a higher transparency (Financial Technology Partners, 2017). Any technology supporting financial advisors is part of the WealthTech segment.

Disruption of the traditional investment management and registered investment advisor (RIA) industries comes from several factors, the upcoming robo-advisors and other online alternative investments managing programs, the change of investment strategies from active to passive, the demand for greater returns by alternative investments, and a changing customer base (more technology using and young investors). Although, the current investment management firms and registered investment advisors know they must respond, it appears that innovation driven by technology isn't their strength. As a result, a large group of FinTech companies has put their focus on these traditional industries. The FinTechs have greater digital capabilities and provide support with enhancing distribution capabilities and underlying operations on an outsourcing basis (Financial Technology Partners, 2017). eFront SA is an example of a European based WealthTech company, which is present in the dataset.

2.3.4 Money transfer/remittance

The companies in this vertical are defined as providers/owners of peer-to-peer platforms to transfer money between individuals across countries and regions (KPMG & CB Insights, 2016). The estimated total amount of recorded remittances for 2015 is more than $601 billion worldwide (Sirkeci & Condick-Brough, 2016). In developing countries there has been a significant growth in the value of the remittances, from less than $75 million in the 1980s to more than $451 billion in 2015 (Sirkeci & Condick-Brough, 2016).

According to the 'Global Money Transfer' report of FT Partners, the non-bank (global) money transfer market can be divided into the 'International Payment Specialists', and the 'Consumer Remittance Providers'. The International Payment Specialists have solutions for businesses and consumers with needs for cross-border and foreign exchange payments. And the Consumer Remittance Providers mostly provide service for workers (without a bank) who send remittance to their native countries. From the report appears that there is disruption within the sector by new, emerging and fast-growing entrants, driven by mobile and other technology-driven solutions (Financial Technology Partners, 2017). Qiwi PLC and Xoom Corp. are examples of companies in the money transfer sector.

2.3.5 Blockchain/bitcoin (cryptocurrencies)

Blockchain and bitcoin companies are key software and/or technology companies in the 'distributed ledger space', ranging from bitcoin wallets to security providers to sidechains (KPMG & CB Insights, 2016). The Bitcoin is a cryptocurrency (non-physical currency) created in 2009, which is traded on online platforms. There exist several other cryptocurrencies, well-known examples are Ethereum and Ripple. These cryptocurrencies are traded 24 hours a day, and transactions are done via platforms on the internet. Blockchain is a (software) technology, used as a 'distributed data store' that holds a large record (public ledger) of all the transactions, for instance all the cryptocurrency transactions (Barberis & Chishti, 2016). Blockchain is the technology behind Bitcoin. From 2014 investors shifted their focus from just Bitcoin, to also the blockchain technology, thereby causing a growth in the usage and familiarity of blockchain (Forbes, 2017).

Some governments and big banks implement blockchains to renew the way information is saved and how transactions are done. Their aim is to achieve higher speed, lower costs, better security, less errors and elimination of common attack- and failure-points. These blockchain models do not have to involve a cryptocurrency for payments, but the most important blockchains originate from the bitcoin model of Satoshi (Tapscott & Tapscott, 2016). Bitcoins or other digital currencies are not stored somewhere in a file or on a website, but are represented by a record of transactions stored in a blockchain, which provides the resources of a large peer-to-peer bitcoin network to verify and approve every bitcoin transaction (Tapscott & Tapscott, 2016).

Companies in this vertical, provide all kinds of different services around bitcoin and blockchain, for example companies offering (online) bitcoin wallets, brokerage services, and other companies try to connect the traditional finance sector with the digital environment of bitcoins and blockchain.

2.3.6 Institutional/capital market tech

Institutional/capital market tech firms provide tools to financial institutions (banks, hedge funds, mutual funds) and other institutional investors, varying from alternative trading systems to financial modeling and analysis software (KPMG & CB Insights, 2016).

Where before the financial crisis the companies in this segment were performing very well, after the crisis (2008/2009) came a less prosperous period during five years, when the market began to heat up with the emergence of lots of startups, ready to present a next wave of technological innovation. The innovation in capital market technology is stimulated by increasingly cheaper cloud computing/storage power, several novel sources of important investment data (among which social media), and competitive forces causing constantly required returns, together with new interest originating from private equity parties and venture capitalists (Financial Technology Partners, 2015).

2.3.7 InsurTech

InsurTechs produce innovation in underwriting, claims, distribution and brokerage platforms, enhanced customer experience and software as a service to help insurers deal with legacy IT issues (KPMG & CB Insights, 2016). According to a PwC report, most of the insurance companies (74% of globally surveyed companies) are aware that FinTech can disrupt and innovate the insurance sector, 43% of the companies claim to centralize FinTech in their corporate strategy, but only 28% have a partnership with a FinTech company. It seems like there is a gap between amount of disruption predicted by the companies and the willingness to invest in it, to either gain from the innovation, or defend against the innovation (PwC, 2016). Nicoletti (2017) also states that the insurance industry has not yet taken full advantage of the available technology, concluding that the insurance industry might even be two to five years behind on the 'digital maturity curve' compared to the financial services industry as a whole (Nicoletti, 2017).

2.3.8 Equity crowdfunding

This vertical consists of platforms that give individuals (investors) the opportunity to contribute in a monetary way, with equity, lending or donations to projects and companies (KPMG & CB Insights, 2016).

CHAPTER 3 FinTech performance

In this chapter discusses previous literature on the short- and long-term performance of IPOs. Theories and explanations of the underpricing and long-term performance anomalies are outlined. And with empirical results of prior research, several hypotheses are drawn.

3.1 The short-term performance (underpricing)

For analyzing the short-term performance of the FinTech IPOs, this thesis will examine the initial first-day average returns, or underpricing. Underpricing is a phenomenon or anomaly, which is present on a lot of stock exchanges worldwide. It is defined as the difference between the closing price on the first trading day and the offer price of the IPO. Because of the long and worldwide presence of underpricing on the stock markets, a lot of literature exists, and a lot of research has been done. The underpricing, and its underlying factors, are the main content of the research of the short-term performance of the FinTech IPOs.

3.1.1 Underpricing

The focus of this thesis is on the IPOs in the USA, Canada (North-America) and Europe. The IPO markets in these regions have been extensively researched on their IPO performance. By discussing the findings of some past researches, expectations of the underpricing in the regions that are analyzed in this thesis, can be formed. Off course it is hard to predict the level of underpricing of the FinTech companies, as there is not a lot of research on the IPO performance of these companies.

According to Ritter (2017) the average underpricing for the period 2001-2016 in the US is 14.0%, ranging from the lowest level of 5.7% in 2008, to the highest level of 21.2% in 2013 (Ritter, 2017). In that period were 1,735 IPOs, among which 569 technology companies. FinTech companies also fall under these technology companies. Furthermore, Ritter’s IPO overview shows that the level of underpricing differs for several time periods. The underpricing for 1980-1989 is 7.3%, 1990-1998 with 14.8%, the internet bubble in the period 1999-2000 has an underpricing of 64.5%, and 2001-2016 with 14.0%. According to Chung, Kryzanowski, & Rakita (2000) Canada has the lowest IPO underpricing of all industrialized countries. Besides, the underwriter fees are lower than, and not as concentrated, as in the US (Chung, Kryzanowski, & Rakita, 2000). From Ritter’s IPO Underpricing overview an average level of underpricing in Canada of 6.50% can be extracted (till 2015). Considering these positive levels of underpricing for the US and Canada, the logical expectation would be that the underpricing of the FinTech companies for these countries (combined) will also be on average positive. As the number of US IPOs is in general higher than the number of Canadian IPOs, the effect of the US FinTechs on the average underpricing of both together countries will be larger than the effect of the Canadian FinTechs on the average underpricing. So, considering Ritter's numbers for underpricing of both countries, the level of North-American FinTech underpricing will be more around the 14.0% of the US than around the 6.50% of Canada.

For the main stock markets in Europe there is evidence for the existence of underpricing. Derrien and Womack (2003) find an average underpricing of 13.23% for the period 1992-1998 in France. Where Ljungqvist and Wilhelm (2002) examined the period of 1990 – May 2000, and find an average underpricing of 16.5% for France and 40.2% for Germany. For Poland evidence is found of an underpricing level of 13.95% when the delisted companies are also used, and an underpricing of 15.78% when the delisted companies are left out the sample, the period is 1998-2008 (Jewartowski & Lizińska, 2012). The researchers mention that the underpricing decreased over the years, when they review the underpricing over time.

Ritter (2017) provides an overview of the underpricing for most European countries up till 2015. Some of the levels of underpricing are: Denmark 7.40% (1984-2011), Finland 16.70% (1971-2013), France 10.5% (1982-2010), Germany 23.00% (1978-2014) and Poland 12.70% (1991-2014). Focus in this thesis is on the IPOs of European FinTech companies in the period 2005-2017. The levels of underpricing mentioned above differ between the countries, for all countries the level of underpricing is positive, so this would be expected for the European FinTechs. The European FinTechs are from several countries, having an advantage that some country-specific effects have a smaller effect on the average underpricing.

The underpricing is the average first-day returns, calculated as the offer price minus the first-day closing price, divided by the offer price. Based on past empirical results of positive levels of underpricing in the past in the US, Canada and several countries in Europe, the underpricing for Europe as well for the US and Canada is expected to be positive. Furthermore, the average underpricing for the North-American companies is expected to be higher than the European underpricing, because from Ritter (2017) appears that the level of US underpricing is usually higher than the level of underpricing of most European countries (Ritter, 2017). Based on the above, hypotheses 1.1 and 1.2 are as follows:

Hypothesis 1.1: FinTech companies have a positive level of underpricing.

Hypothesis 1.2: The North-American FinTech companies have a higher level of underpricing than the European FinTech companies.

3.1.2 Asymmetric information model of Baron (1982)

An explanation for underpricing comes from the ‘Model of the Demand for Investment Banking Advising and Distribution Services for New Issues’ of Baron (1982). It builds on the information asymmetry between the issuer and underwriter. The underwriter of an IPO has better information about the right price for the IPO shares, as he is better informed about the demand by investors on the capital market for those specific shares. If the issuer is more uncertain about the equilibrium price of its shares, the demand for the advice of an investment bank will be greater. But, the underwriter has incentives to advice an offering price under the market-clearing price, because underpricing reduces the work it costs to sell the shares, and lowers the probability that the underwriter has to take the shares that are not sold. So, the model states that if the uncertainty about market-clearing prices is larger, the average underpricing of the IPOs will also be larger (Ruud, 1993).

3.1.3 The Winner’s Curse

“Ex ante uncertainty is defined as the uncertainty about the offering’s value once it starts trading”, and is an important and common mentioned cause for underpricing (Kooli & Suret, 2001). One of the important models that use ex ante uncertainty to explain underpricing, is the model of Rock (1986) which is called the theory of the Winner’s curse.

The Winner’s curse relies on the information asymmetry between the two types of investors on the market, namely the institutional investors (most of the time relatively better informed) and the private investors, which results in an adverse selection bias. The institutional investors know when an IPO is relatively expensive, and therefore won’t subscribe on it, whereas the private investors will subscribe on any IPO as they don’t have this (costly) knowledge. Consequently, the (more) expensive IPOs will be allocated to the private investors. Because both type of investors behave strategically, a ‘discount’ or ‘premium’ is required to compensate the private investors, which results in a lower introduction price.

Beatty and Ritter (1986) expanded the Winner’s curse theory of Rock (1986), and argued that if the market value of an IPO is higher, the level of underpricing will increase as well. Beatty and Ritter assign importance to the role of the underwriter of the IPO for the presence of an equilibrium between the degree of underpricing and the degree of ex-ante uncertainty. Investment bankers lose clients, and thereby market share, if they price the shares relatively high from investor’s viewpoint, also called ‘pricing off the line’ (Beatty & Ritter, 1986). Therefore, the underwriter tries to keep the investors, as well as the offering firm satisfied, to hold its market position, leading to inefficient pricing of the shares (Beatty & Ritter, 1986).

3.1.4 The relation between ex ante uncertainty and underpricing

Ex-ante uncertainty is not measurable with one single variable, and is/can be affected by many factors. This implies that (some of) those factors should be tested as proxy variables to measure ex-ante uncertainty. A selection of factors is made, and regressed on the underpricing of the FinTech companies, to examine what their effect (sign and significance) is. The factors are regressed in several multivariate regressions, explained in section 5 Methodology. An important requirement of the factors is that they should be observable.

Clarkson and Merkley (1994) examine the relation between ex-ante uncertainty and the level of underpricing for IPOs in Canada for the period 1984-1987. From their results appears that if a firm has more ex-ante uncertainty, the level of underpricing is larger. This is tested by using several variables as proxies for ex ante uncertainty. Some of these variables have a significant negative effect on underpricing (the annual-sales-level, gross proceeds, auditor quality, and underwriter prestige) and another one (size of the underwriters' fee) has a positive effect.

A positive relation between underpricing and ex-ante uncertainty is found by Clarkson (1994), which involved a direct relation between ex ante uncertainty and the degree of underpricing (Clarkson, 1994). 'Firm age in years' and the 'number of risk factors listed in the prospectuses' are significant proxies for ex-ante uncertainty. The results also imply that if a selected proxy as measure of ex-ante uncertainty increases in effectiveness, the strength of the relation between the level of underpricing and ex-ante uncertainty, as measured by that proxy, increases. This is powerful support for a direct relation between the degree of underpricing and the level of ex-ante uncertainty (Clarkson, 1994).

Wasserfallen and Wittleder (1994) find that the 'standard deviation of returns in secondary market' has a significant positive effect on the underpricing. Further they tested several ratios, like cash flow/sales and return on net worth, but none of them has a significant effect, remarkable is that all the ratios appear to have a negative effect (Wassenfallen & Wittleder, 1994).

3.1.5 Other explanations

There exist many other explanations for underpricing, like the costly information acquisition hypothesis by Benveniste and Spindt (1989), the signaling hypothesis from Welch (1989), there are behavioral explanations like the 'Information cascades' of Welch (1992) and 'Investor sentiment' by Lunqvist, Nanda and Singh (2004).

3.1.6 Difference US and European IPO market

The US and European stock markets have several differences, that will not be discussed here, for example different regulation, currencies, investment bankers, investors, and the number of IPOs each year. The US stock markets are characterized by large IPO activity, probably there are nowhere else as much IPOs each year as in the US. Analogously this is observable from the dataset of this thesis, where the number of FinTech IPOs in the US (even when not taking Canada into account) is almost twice as big as the number of FinTech IPOs in Europe. Therefore, it will be interesting to see what effect the differences between the US and the European IPO markets will have for the empirical results.

Ritter (2003) has surveyed the differences between the American and the European markets. It appears that the gross spreads that are paid by companies to the underwriting investment banks are lower in Europe. Further, in the US there is a ‘quit period’, in which analysts that were involved with the underwriter are not allowed to issue researches, reports or recommendations, the period lasts from the moment that the company decides to go public till 40 days after the IPO (Ritter, 2003). The methodology to price an IPO differs between US and Europe and even within Europe between the different countries.

3.1.7 Ex-ante uncertainty proxies

Many factors have been tested as ex-ante uncertainty proxy on underpricing. As prior research has not focused on the FinTech sector, and usually in general not on specific sectors, it is hard to choose ‘right’ variables as ex-ante uncertainty proxies. In this thesis, the following factors are chosen, based mostly on common usage of proxies: as company characteristics, company age and company size; as offering characteristics, proceeds, venture backed, underwriter reputation and hot or cold IPO market; as prospectus disclosure, the number of uses of proceeds; and as after market volatility (ex post uncertainty) factors, the standard deviation and the trading volume.

Firm age

The age of the company at the time of the IPO, is calculated as the number of years between the first trading date and the founding date. Following empirical results from the past, the underpricing should be negatively correlated with the firm’s age. Ritter (1991) and Barry, Muscarella, and Vetsuypens (1991) state that a firm’s age (measured the same way as in this thesis) has a negative relation with ex-ante uncertainty. Clarkson and Merkley (1994) used for a Canadian dataset, company age as ex-ante uncertainty proxy, their results show that age has a negative relation with underpricing. Also, Schenone (2004) found a negative relation between the firms’ age and the level of underpricing for US firms with an IPO in the period 1998-2000. The age of a company can contain a lot of information, besides the longer a company exists, the more information about performance, management, growth, and more is available. The hypothesis regarding the effect of firm age on underpricing is:

Hypothesis 1.3: When a FinTech company is older, the level of underpricing is lower.

Firm size (Market Capitalization)

To measure firm size, the market capitalization of the firm is taken as variable, which is defined as the number of shares outstanding times the share price, at a specific date. The choice for market capitalization is made, because there is missing information for some companies about the total assets before the IPO. Previous empirical findings of researches on IPO underpricing, has shown that the size of a company has a negative relation with the underpricing of the IPO (Schenone, 2004). Larger firms have a lower chance of financial distress and are more likely to reissue stocks (Garfinkel, 1993). Besides, there may be a positive correlation between firm-specific information in the market and firm size, which implies that there is lower ex-ante uncertainty for larger firms (Garfinkel, 1993).

Hypothesis 1.4: The underpricing is negatively correlated with the size of a FinTech company.

Proceeds

Beatty and Ritter (1986) use the gross proceeds as proxy for ex-ante uncertainty. It frequently appears that smaller offerings are more risky than larger offerings (Beatty & Ritter, 1986). Different from Beatty and Ritter (1986), who use the inverse of the proceeds, this thesis uses the natural logarithm of the proceeds. Hypothesis 1.5, regarding the proceeds, is:

Hypothesis 1.5: The higher the proceeds of an IPO, the lower the underpricing.

Number of uses of proceeds

The number of uses of proceeds is mentioned in the IPO prospectus of the firm, and can vary from not mentioned to several allocations for (expected) production or investment decisions. Beatty and Ritter (1986) take the number of uses of proceeds as ex-ante uncertainty proxy, by explaining that the SEC requires more speculative issuers to provide relatively more and more detailed information about the usage of the proceeds, in comparison with the more established issuers. Therefore, a higher number of uses of proceeds is suggesting a higher ex-ante uncertainty:

Hypothesis 1.6: The higher the number of uses of proceeds, the higher the underpricing.

Venture backed IPO

Not all companies are backed by venture capital, this probably influences the underpricing of those companies. Empirical work from Barry et al (1990), provides evidence for a negative relation between underpricing and venture backed firms. Venture capital investors aim with their investments on intensive monitoring roles in firms. With the monitoring role comes a concentrated equity position, a sustainable monitoring role after the IPO and participation in the boards of the invested companies (Barry, Muscarella, Peavy III, & Vetsuypens, 1990). Capital markets identify the quality of this monitoring, which results in a lower level of underpricing for companies which are monitored better (Barry, Muscarella, Peavy III, & Vetsuypens, 1990). On the other hand, it appeared that unexperienced venture capitalists take companies public too early, a phenomenon also called ‘grandstanding’ (Berlin, 1998). Which makes investors willing to pay less for the stock, resulting in a lower price. Following the discussed effect of venture capital on a firm, hypothesis 1.7 is as follows:

Hypothesis 1.7: The underpricing of a venture capital backed firm’s IPO is lower than that of a non-venture capital backed firm.

Hot or cold issue market

Existence of IPO market cycles can be explained following the literature. For instance, clusters of IPO in new industries, signaling theories, but also the economic state can have an important role. A common measure of the IPO activity is issue volume, which is used in this research. The number of IPOs per year, within a certain period, suggest when there is a hot or cold period. To determine when there is a hot (or cold) period, the average monthly issue volume is calculated, and the average proportion of the IPOs per month for each year. Then is determined which years have a high or low average proportion of IPOs per month, when there is a high average proportion of IPOs for the months in a year, this year is marked as a period of a hot market. Because the hot and cold markets are in cycles, periods of several years of high issue volumes are alternated by periods of low issue volumes. Because of the presence of the Global Financial Crisis in the research period of 2005-2017, there are hot and cold market cycles in the data, with the crisis as a cold period.

Underwriter reputation

Carter and Manaster (1990) did research on IPOs and the reputation of the underwriters. They provide empirical proof that when there are more, better informed, investors, higher returns on the IPOs are required. The reputation of the marketing underwriter, indicates the expected level of "informed" activity (Carter & Manaster, 1990). Underwriters with a good reputation are often associated with offerings of lower risk, and when there is less risk, investors are less motivated to gather information, and so there are less informed investors. Consequently, underwriters with a good reputation are associated with IPOs of lower (initial) returns. Moreover, earlier was stated by Beatty and Ritter (1986) that the underwriters have a stake in maintaining their reputation, because they are afraid to lose potential investors, and therefore enforce the underpricing equilibrium (Beatty & Ritter, 1986).

To determine if the underwriter of the firm's IPO underwriter had a good reputation, a ranking of investment banks presented in a research by Griffin, Lowery and Saretto (2014) is used. They provide a table with reputational investment banks and a corresponding rank, ranging from 1-9. Investment banks with a poor reputation have no ranking. If the underwriter of the IPOs in the dataset of this thesis has at least a ranking of 1 in the Griffin, Lowery and Saretto (2014) research, a dummy value of 1 is assigned to that observation. So, the rank is translated into the dummy variable.

Aftermarket liquidity

As last two variables are used as ex-ante uncertainty proxies, reflecting the liquidity on the market after the IPO. Variables 'Trading volume' and 'Standard deviation'. When the stock of an IPO is less liquid, this is indicated by a low trading volume and a high standard deviation, there will be more ex-ante uncertainty. The standard deviation is the average standard deviation of the stock prices, averaged over the first twenty trading days after the IPO. And trading volume is measured by the average turnover by volume, averaged over the first half year after the IPO.

3.2 Long-term underperformance

Another anomaly regarding the performance of initial public offerings, is the long-term underperformance of IPOs, which implies the bad performance of the returns of IPOs in the long run. Generally, poor performance of stocks over a certain period after an IPO, reflects that the investors were overoptimistic about the information that came public on the IPO day (van der Sar, 2015). The occurrence of long-term underperformance is suggesting that there is another explanation for underpricing than ex ante uncertainty, namely excessive optimism (van der Sar, 2015).

Most of the underpricing explaining theories, which are relying on the assumption of rational behavior, are not relevant for the development of after-market returns. This is different when investors behave irrationally caused by excessive optimism (van der Sar, 2015). When irrational behavior is seen on the IPO day (first trading day), implicated by underpricing, a market tendency of restoring an equilibrium would carry out itself by a proportionate price correction downwards (van der Sar, 2015).

There are several factors that make the long-term performance of IPOs interesting. First, there is importance for investors, because if there exist price patterns, it may reflect possible opportunities that are useful for active trading strategies to achieve (positive) abnormal returns (Ritter, 1991). Secondly, if a good aftermarket performance is found, this leads to doubts about the efficiency of information of the initial public offering market. And then it will strengthen the hypothesis of Shiller (1990) that, particularly IPO markets, and equity markets in general suffer from fads that affect market prices (Ritter, 1991). Third, the IPO activity varies largely over time. When periods with a lot of IPO activity (hot markets) are associated with a bad long-term performance, this would provide an indication that companies are timing their IPOs with success, so they make use of the "windows of opportunity" (Ritter, 1991). And as last, the cost of external equity capital for firms that go public, is not only depending on the transaction costs of the IPO, but also on the returns that investors make in the aftermarket (Ritter, 1991). The cost of equity capital is adjusted downwards for these firms, against the level that low returns are made in the aftermarket (Ritter, 1991).

Empirical support for the long-term performance anomaly is provided by Loughran and Ritter (1995), who find an underperformance of 51% over a five-year period in the US (from 1970-1990). Their evidence is consistent with a market where companies are making use of passing windows of opportunity, through issuing shares during a period when the shares are on average substantially overvalued (Loughran & Ritter, 1995). Other evidence is provided by Ritter and Welch (2002), who find a post-IPO long-term underperformance of 23.4 percent over a three-year period measured against the CRSP value weighted market index, for the period 1980-2001, and an underperformance of 5.1

percent against seasoned companies with comparable book-to-market ratio and market value (Ritter & Welch, 2002).

3.2.1 Explanations for the long-term (under)performance

Generally, the underperformance of a stock over a specific period after an event, reflects an overoptimistic rating of the information that becomes public on the day of the event (van der Sar, 2015). The over optimism does not become 'visible', until the market reacts, resulting in a price correction.

The 'windows of opportunity' hypothesis, introduced by Ritter (1991), suggests that firms are trying to make use of the volatility in the market sentiment, by selecting an appropriate moment for their IPO, or try to time their IPO. Another explanation called 'window dressing', states that company-owners or sellers can create an advantageous image of a firm, by the way of showing the past results of the firm (van der Sar, 2015).

3.2.2 Remark on the venture backed FinTechs

Some academics and venture capitalists themselves, think that the pressure to bring companies to the stock market, is promoting the usage of very short time horizons (Berlin, 1998). Furthermore, they state that the pressures have increased with the participation of institutions, like pension funds, in VC funds. These pressures can cause fund managers aiming at short-term payoffs (Berlin, 1998). Eventually the pressures on the fund manager will be transferred to the venture capitalist. Chris Myers, CEO of FinTech Company, BodeTree, writes articles on FinTech for Forbes. He emphasizes the short-term thinking of companies and investors in the FinTech (investment) environment. He states that for some companies there seems to be a so called 'growth-at-all-cost attitude of mind', which is damaging the sector, because using the investment dollars for quick (short-term) growth instead of for innovation, leads to problems in the long run (Myers, 2017).

The short-term thinking in the FinTech sector can relate to the venture capital firms having pressure on realizing short-term returns. It turned out that unexperienced venture capitalists take companies public too early, in trying to create a reputation, this phenomenon is called grandstanding (Berlin, 1998). Which has negative effects for the initial firm-owner as well as for the venture capitalist, because when a company goes public too early, investors are willing to pay less for the stock of the company. A lower price for the company's stock is not the only problem. Performing a too early IPO, will lead to a reduction of the chance on success in the long run.

It often appears that venture backed companies perform better than non-venture backed companies. Evidence is, among others, provided by Ritter (1991) and Loughran and Rittter (1995), who show that the IPO underperformance, comes largely from smaller, non-venture backed companies. Furthermore, Brav and Gompers (1997) replicated the results of Loughran and Ritter (1995), showing empirical evidence that the returns of the IPOs of non-venture backed companies significantly underperform, not only the IPO returns of venture backed companies, but also those of relevant benchmarks (Brav & Gompers, 1997).

Viewing the past empirical evidence for the existence of the long-term underperformance of IPOs, and taking into consideration the potential effect of venture capital investors on the FinTech companies, the hypotheses are as follows:

Hypothesis 2.1: FinTech IPOs will underperform on the long-term (measured over one-year and three-year periods)

CHAPTER 4 Data

To compose a dataset, consisting of 96 North-American (US and Canadian) and 41 European FinTech companies with an IPO between 2005-2017, several steps have to be undertaken. After describing how the list of FinTech companies is created, the data of the companies will be discussed.

Before doing the analysis, a list of the FinTech companies with an IPO between 2005 and 2017 must be created. The FinTech sector does not have its own SIC or NAICS-code, and consists of several different verticals, so the companies had to be found and filtered manually. Next, the steps are described that are undertaken to come to the current dataset.

As a start, all the financial companies with an IPO between 2005 and 2017 in the US and Canada (apart from the Europe) are collected via Thomson-One. This provides a large list of companies in the financial services sector, with among them several FinTech IPOs. To filter the FinTech companies from this list, the database of Financial Technology (FT) Partners (2016), covering most of the US and Canadian FinTech IPOs from 2005 up till now, is used. Next to the FT Partners database, existing FinTech indexes are used to filter the FinTech companies from the list of financial companies. This leads to a list of FinTech companies, via Thomson-One. But several companies with an IPO in the period 2005-2017, was not on the list of Thomson-One, therefore the companies in the FT database and the companies on the FinTech indexes, with an IPO within the period 2005-2017, are also added to the list. The used FinTech indexes are the Nasdaq KBW Financial Technology index and the indexes of the CedarIBS FinTech Index, which are the CIFTI50, CIFTI Large Cap, CIFTI Mid Cap and CIFTI Small Cap.

Furthermore, several FinTech reports, articles, and more are used to search for FinTech companies with a listing. But it appeared that the number of companies with a listing has a minority stake in the total number of FinTech companies.

This procedure is followed twice, once for US and Canadian companies and once for European companies. For the European companies, all European companies are taken into account, to gather a dataset as large as possible, but as will appear the number of European FinTechs with a listing is smaller than the number of North-American FinTechs with a listing. Finally, the dataset consists of 96 North-American FinTechs and 41 European FinTechs. The FinTech companies in the used dataset are from: Denmark, Finland, Germany, France, Luxembourg, Poland, Spain, Turkey, UK and Sweden.

After constructing a list of FinTech companies with an IPO between 2005 and 2017, the required data for regressions on the underpricing must be extracted. The following data is extracted via Thomson-

One, founding date of the company, proceeds, market capitalization, the number of uses of proceeds, name of the underwriter(s), and if a company is backed by venture capital. When the founding date of a company was not available in Thomson-One, it is extracted via Google Finance. The following data is retrieved via Datastream, the base date (IPO date or date of the first trading day) the first trading day closing price, the trading volume (by the turnover by volume), standard deviation of the stock price (by retrieving the closing prices of the first 20 trading days). When crucial data, like the IPO date, offer price or the first-day closing price is not available or missing for a certain company, this company is deleted from the dataset. With the formula discussed in section '3.1 Underpricing', the underpricing is calculated. Other data that is retrieved from Datastream are the closing prices of the first 20 trading days, to calculate the standard deviation of the stocks, and the turnover by volume, to calculate the trading volume. An overview of all the IPOs and the corresponding data can be found in Appendix 1A (North-American companies) and Appendix 1B (European companies).

For the long-term performance, the number of observations declines over time, because of recent listing date, an acquisition, bankruptcy or other reasons. The stock prices of three years after the IPO are extracted via DataStream. Which are the stock prices up till the 758th trading day, implying that there are about 21 trading days per month, following Ritter (1991).

4.1. Descriptive statistics

Before discussing the results, the descriptive statistics are presented. Among others, extreme values are detected and discussed. For the short-term performance, the data is presented in two tables (datasets), a Europe and a North-American dataset.

Table 4.1: Descriptive statistics of European companies

Variable	Mean	Median	Maximum	Minimum	Std. Dev	Observations
Underpricing	0.10	0.05	0.85	-0.73	0.23	41
Age (years)	14.60	8.31	163.47	0.08	26.31	39
Market Cap (thousands)	2500723.00	282250.00	30282110.00	370.00	5893434.00	41
Proceeds (millions)	355.52	69.57	2371.81	0.03	576.94	41
# use of proceeds	2.17	2.00	7.00	1.00	1.63	41
Std. dev of stock	3.55	1.26	14.85	0.05	4.34	41
Trading volume	684.48	125.96	8632.52	0.09	1710.22	39

In table 4.1 the descriptive statistics of the European companies are presented. The minimum (-0.73) and maximum (0.85) underpricing are far apart, but not odd, and match with the high standard deviation of 0.23. Another value that is attracting attention is the maximum value of age of 163.47, which seems very high for a FinTech company. The high value of age is for the company Euronext NV, which is founded in 1851. This observation will not be deleted from the dataset, because Euronext NV is an old company, but due to its operations as a stock exchange company it must constantly adapt (innovative) financial technology, therefore Euronext NV is assumed to be a FinTech company. Besides this relatively extreme value will be weakened in the regressions, because as variable ln (1+age) is regressed on the underpricing instead of age. Obviously, there is a very wide range in the age of European FinTech companies, from the maximum of 163.47 years of Euronext NV to the minimum age of 0.08 years of Mobile Credit Baltic Plc.

The last value that catches attention is the minimum value of proceeds of 0.03 million, which is of the company Woogroup SA. Same as with the age, not the proceeds but the ln of the proceeds will be used in the regressions, thereby the effect of this low value is minimized. A big range in the proceeds is visible, with a maximum of 2371.81 millions of Nets A/S. Furthermore, in market capitalization (firm size) there is a big difference between the minimum (370,000 of Financial Payment Systems Ltd) and maximum value (30.3 billion of Nets A/S).

Table 4.2: Descriptive statistics of US/Canadian companies

Variable	Mean	Median	Maximum	Minimum	Std. Dev	Observations
Underpricing	0.17	0.14	1.25	-0.88	0.30	94
Age (years)	15.26	10.88	157.80	0.27e^-3	19.61	94
Market Cap (thousands)	6435779.00	1513140.00	1.75e^8	80.00	22559446.00	94
Proceeds (millions)	485.13	139.65	17864.00	0.20	0.00	94
# use of proceeds	3.80	4.00	8.00	1.00	2.00	94
Std. dev of stock	1.09	0.69	11.80	0.00	1.62	94
Trading volume	1490.60	277.78	61133.61	4.33	6806.32	94

As is obvious from tables 4.1 and 4.2, the number of North-American FinTech companies, with an IPO in the period of 2005-2017, is substantially larger than the number of European FinTechs.

From the descriptive statistics of the North-American companies there appears to be a relatively high maximum value of age. As this is from a comparable company as Euronext NV, namely NYMEX holdings, no further explanation is needed. Furthermore, the minimum value of Market Cap of 80 thousand seems low, but this value is the actual market capitalization of Liquid Holdings Corp.

The big range between the minimum value of the underpricing, -0.88 of MasterCard Inc., and the maximum value of underpricing, 1.25 of NYMEX Holdings Inc., show that the North-American FinTech underpricing differs widely. This range matches the high standard deviation of 0.30.
The market capitalization of the firms is within a wide range of $17.5 billion, of Visa Inc., till a minimum of $80 thousands of Liquid Holdings Group Inc., which also explains the high standard deviation of $2.25 billion.

The average proceeds of the North-American FinTech companies, $485.13 million, is substantially higher than the average proceeds of the European FinTechs, of $355.52 million. Also, the average number of uses of proceeds of North-American companies, 3.80, is higher than that of the European companies, 2.17. Furthermore, the average value of the standard deviation of the stock (1.09) of the North-American FinTechs are about three times as low as the average standard deviation of the stocks (3.55) of the European FinTechs. But the average trading volume (1490.60) of the North-American companies is more than two times as large (the difference is 806.12) as the average trading volume of the European companies (684.48).

The average age of the FinTech companies of both regions is not differing largely, the North-American firms have an average age of 15.26, where the European firms have an average age of 14.60. And in both regions the maximum age is above 155 years.

The difference in the data between the companies from both regions will be visible in the results, presented in section 6. The levels of underpricing will be tested on their statistical significance, which makes it possible to draw conclusions on the difference in the underpricing, and in the performance on the long-term, between the two regions.

For two companies, Cachet Financial Solutions Inc. and Planet Group Inc., not the right first-day closing prices could be extracted via Datastream (check with google finance). Therefore, these observations are left out of the short-term dataset, and not from the long-term dataset, because the performance is then not measured against the offer price.

CHAPTER 5 Methodology

The results part of this thesis is separated in two parts, one part the short-term performance and a second part with the long-term performance. For both the short-term performance, the underpricing is calculated and used in multivariate regressions with several variables. The long-term performance is examined with average adjusted (cumulative) abnormal returns and average buy-and-hold abnormal returns. This chapter starts with the methodology of the short-term performance, where after the calculation of the (cumulative) abnormal returns, and discusses as last the methodology of the average buy-and-hold abnormal returns.

5.1. Underpricing

First part in examining the short-term performance is calculating the underpricing. The underpricing is calculated with the following formula:

$$\text{Underpricing} = \frac{\text{First day closing price} - \text{Offer price}}{\text{Offer Price}} \qquad (1)$$

The second part of the short-term performance is testing of the ex-ante proxies on the underpricing. The underpricing is used as dependent variable in several multivariate regressions, which are build up in a specific way. The first regression is with two variables, the natural logarithms of firm age added with 1 (1+age) and market capitalization (denoting firm size). These variables reflect the company characteristics.

$$\text{Underpricing} = \propto + \beta_1 * \ln(1 + \text{age}) + \beta_2 * \ln(\text{Marketcap}) + \varepsilon_t \qquad (2)$$

In regression (2) four deal characteristics are added, among them are three dummy variables, namely for a venture capital backed IPO (1 if venture backed), a hot or cold IPO market (1 in case of a hot market), and the underwriter reputation (1 if underwriter has a good reputation). The fourth variable added, is the natural logarithm of the proceeds of the IPO. These variables are reflecting characteristics of the IPO.

$$\text{Underpricing} = \propto + \beta_1 * \ln(1 + \text{age}) + \beta_2 * \ln(\text{Marketcap}) + \beta_3 * D1_{\text{Venture}_{\text{capital}}} + \beta_4 * D2_{\text{Hot or cold market}} + \beta_5 * D3_{\text{Underwriter reputation}} + \beta_6 * \ln(\text{Proceeds}) + \varepsilon_t \qquad (3)$$

In regression 3, the variable number of uses of proceeds, is added to the regression model 2. Uses of proceeds contains information about the prospectus disclosure of an IPO.

$$\text{Underpricing} = \propto\ + \beta_1 * \ln(1 + \text{age}) + \ \beta_2 * \ln(\text{Marketcap}) + \ \beta_3 * \text{D1}_{\text{Venture}_{\text{capital}}} + \ \beta_4 * \text{D2}_{\text{Hot or cold market}} + \ \beta_5 * \text{D3}_{\text{Underwriter reputation}} + \ \beta_6 * \ln(\text{Proceeds}) + \beta_7 * (\#\ \text{uses of proceeds}) + \varepsilon_t \qquad (4)$$

In the last regression model, the effect of the after-market volatility on the underpricing is tested, by adding the variables trading volume and the standard deviation of the stocks.

$$\text{Underpricing} = \propto\ + \beta_1 * \ln(1 + \text{age}) + \ \beta_2 * \ln(\text{Marketcap}) + \ \beta_3 * \text{D1}_{\text{Venture}_{\text{capital}}} + \ \beta_4 * \text{D2}_{\text{Hot or cold market}} + \ \beta_5 * \text{D3}_{\text{Underwriter reputation}} + \ \beta_6 * \ln(\text{Proceeds}) + \beta_7 * (\#\ \text{uses of proceeds}) + \beta_8 * \sigma_{\text{first 20-days}} + \ \beta_9 * \text{trading volume} + \varepsilon_t \qquad (5)$$

From the regression results, the effects of the variables on the underpricing are derived. Depending on the t-statistics is concluded if a certain effect is (statistically) significant. When the effect of the variables is in line with the predicted effect, discussed in Section 3, the corresponding hypotheses can be accepted.

5.2. Long-term event study

To evaluate the long-term performance of the FinTech IPO's, the cumulative average adjusted returns (CAR), with monthly rebalancing the portfolio in the calculation, following the methodology of Ritter (1991), next to the buy-and-hold returns, as described in Van der Sar (2015), are used.

5.2.1 (Cumulative) Abnormal returns

The returns are calculated for two intervals, a one-year period and a three-year period, after the IPO. The IPO day is not included in the calculation of the returns over this interval. A month is assumed to consist of 21 trading days. This implies that the first month comprises trading day 2-22, the second month comprises day 23-43, etc. Because some firms are not listed for one or three years, their returns are calculated up till the maximum available month of their listing. The benchmark-adjusted returns are calculated up to the date of delisting or the date which is maximally possible, calculations of future returns cannot be made.

The monthly benchmark-adjusted returns are calculated as the monthly raw return on a stock minus the monthly benchmark return of the associated trading period. The adjusted returns are calculated using two different benchmarks, for the North-American companies, the NASDAQ, and for the European companies the STOXX Europe 600 Tech index, are used. The selection of these technology indexes as benchmarks is because FinTech companies are also tech companies. The benchmark-adjusted return for one stock i, in the IPO month t, is defined as follows:

$$\mathrm{ar}_{\mathrm{it}} = \mathrm{r}_{\mathrm{it}} - \mathrm{r}_{\mathrm{mt}} \qquad (6)$$

In this thesis, the monthly benchmark-adjusted returns per company are specified as the equally weighted average of the adjusted returns of all trading days in the month. So, per company is for each month, the average benchmark-adjusted return calculated:

$$\mathrm{ar}_{\mathrm{it}}' = \frac{1}{\mathrm{n}}\sum_{\mathrm{i}=1}^{\mathrm{n}} \mathrm{ar}_{\mathrm{it}} \qquad (7)$$

The average benchmark-adjusted returns for all the number of companies (n) in the dataset (or portfolio) in the IPO month t, is displayed by the sum of the equally weighted average of the benchmark adjusted returns of all companies:

$$\mathrm{AR}_{\mathrm{t}} = \frac{1}{\mathrm{n}}\sum_{\mathrm{i}=1}^{\mathrm{n}} \mathrm{ar}_{\mathrm{it}}' \qquad (8)$$

With the average benchmark-adjusted returns, the cumulative benchmark-adjusted (CAR) can be calculated. CAR is a good indicator of the stock performance of a certain period, if the CAR is positive, the stock has performed well and if the CAR is negative, it indicates a bad performance over the measured period. The cumulative benchmark-adjusted return, measured from month k to month s, is defined as the sum of the AR_t's:

$$\mathrm{CAR}_{\mathrm{k,s}} = \sum_{\mathrm{t}=\mathrm{k}}^{\mathrm{s}} \mathrm{AR}_{\mathrm{t}} \qquad (9)$$

When a stock has not reached a listing of three (or even one) years, the available benchmark-adjusted returns are included in the calculation of the CAR. When a firm is delisted from the data, the remaining companies in the portfolio form with their equally weighted average the return on the portfolio for the next month. This way, the portfolio is monthly rebalanced. When the CAR is calculated, it is tested on its significance, with the following t-test:

$$\mathrm{t}(\mathrm{CAR}_{\mathrm{t}}) = \frac{\mathrm{CAR}_{\mathrm{t}}\sqrt{\mathrm{n}}}{\sqrt{\mathrm{t} \times \mathrm{var} + 2 \times (\mathrm{t}-1) \times \mathrm{cov}}} \qquad (10)$$

5.2.2 Buy-and-hold abnormal returns

The cumulative abnormal return approach is generally more useful for measuring short term performance of IPOs (or other events), moreover the CAR method has several disadvantages. With the approach of cumulative abnormal returns the 'stock portfolio' is constantly rebalanced at the end of every individual period (day, week or month). This doesn't give a good representation of a real investment strategy (van der Sar, 2015). Therefore, another more appropriate measure for testing the long-term performance of stocks is used, namely the buy-and-hold abnormal returns (BHAR). The buy-and-hold returns are the cumulative returns of a stock portfolio of a certain period, the BHAR is calculated without periodically rebalancing.

The buy-and-hold return of a stock I over period (K, L) is defined as the buy-and-hold return of stock i minus the buy-and-hold return of a certain benchmark over the measuring period:

$$BHAR_{\mathrm{iKL}} = \prod_{\mathrm{t=K}}^{\mathrm{L}}(1 + \mathrm{R}_{\mathrm{it}}) - \prod_{\mathrm{t=K}}^{\mathrm{L}}(1 + \mathrm{R}^{*}_{\mathrm{t=K}}) \qquad (11)$$

The buy-and-hold abnormal returns will be tested over two different time periods, a one-year and a three-year period. For the North-American companies the NASDAQ index is used as benchmark and for the European companies the STOXX Europe 600 Technology is used as benchmark. The average buy-and-hold abnormal return is defined as:

$$\mathrm{BHAR}_{\mathrm{KL}} = \frac{1}{\mathrm{N}}\sum_{\mathrm{i=1}}^{\mathrm{N}} \mathrm{bhar}_{\mathrm{iKL}} \qquad (12)$$

For testing the null-hypothesis, that the buy-and-hold abnormal return over period (K, L) is zero, the following test is used:

$$\mathrm{TBHAR}_{\mathrm{KL}} = \frac{\mathrm{BHAR}_{\mathrm{KL}}}{\mathrm{s}_{\mathrm{bh}}/\sqrt{\mathrm{N}}} \qquad (13)$$

CHAPTER 6 Results

This section discusses and presents the results. Section 6.1 discusses the short-term IPO FinTech performance, with first, the short-term performance of the North-American FinTech companies, second, the short-term performance of the European companies, and as last, the short-term performance of the FinTechs of both regions combined. After the short-term performance, the long-term IPO performance is examined over one-year and three-year periods, in section 6.2.

6.1. The short-term performance of FinTech companies

6.1.1 Underpricing

The level of underpricing for a specific region or dataset is indicated by the average underpricing of all the companies. When this mean differs significantly from 0, there is significant underpricing. To be able to accept or reject hypothesis 1.1, which is: “There is a positive level of underpricing for FinTech IPOs”, the different levels of underpricing, reported in table 6.1 below, are tested on their significance. The North-American FinTech companies are significantly underpriced with 17%, and the European companies are significantly underpriced with 10%. The companies of both regions together, have a significant level of underpricing of 15%. Following this result, hypothesis 1.1 can be accepted. To compare the underpricing of the European companies and the underpricing of the North-American companies, a mean comparison t-test is performed, which provides evidence that the underpricing of the North-American companies is significantly higher (on a 90% confidence level) than the underpricing of the European companies, see Appendix 1C.

Table 6.1: Overview of underpricing

Region	Underpricing (*100%)	t-statistic	Std. Dev
US/Canada	0.17	5.61***	0.30
Europe	0.10	2.63**	0.23
Combined	0.15	6.16***	0.28

***significant on 1%-level, ** significant on 5%-level, * significant on 10%-level

According to Ritter (2017) the level of underpricing in the US for the period 2001-2016 is 14.0%. Comparing this level of underpricing with the overall level of underpricing of the FinTech companies, there is a difference of only 1.0%. But when comparing it to the average underpricing level of 17.3% of North-America, there is a substantial difference of 3.3%. Taking the level of underpricing of Canadian firms of 6.50% (Ritter, 2017), the FinTech companies obviously are more underpriced, but the number of Canadian FinTech companies in the dataset is substantially lower than the number of US FinTech companies, therefore the Canadian firms have a smaller effect on the level of underpricing.

Table 6.2 reports the average level of underpricing per year, and the number of IPOs per year. The highest level of underpricing for the North-American companies is in 2012 with 38.4%, and the European highest level of underpricing is 58.3% in 2011, which comes from only one IPO this year. There is a big range between the lowest values of underpricing of both regions. The lowest underpricing of North-American IPOs is 8.5% in 2007, against the lowest European underpricing of -73.4%, caused by one IPO in 2009. The highest number of IPOs for North-American FinTechs is 13, in the years 2005, 2014 and 2015, where the highest number of European FinTech IPOs is 8 in 2007 and 2014. The periods of higher number of IPOs are roughly the same for both regions, 2005-2007 and 2013-2017 seem to be relatively hot periods for FinTech IPOs. Only in 2010 (11) and 2012 (10) the number of North-American IPOs is much higher than the number of European IPOs (respectively 1 and 0). The average proceeds of the North-American FinTech companies seem to be lower than before 2009, in 2008 and 2009 there were two large IPOs, of Visa Inc. and Verisk Analytics Inc. The average proceeds of the European FinTechs are more volatile over the years, caused by the low number of observations.

Table 6.2: Average underpricing per year of all FinTech companies in the dataset

	North-America			**Europe***		
Year	**Mean first-day return**	**Number of IPOs**	**Average proceeds (millions)**	**Mean first-day return**	**Number of IPOs**	**Average proceeds (millions)**
2005	11.8%	13	191.2	16.0%	3	40.8
2006	11.4%	7	482.7	22.0%	6	508.4
2007	8.5%	5	425.6	12.4%	8	73.4
2008	32.1%	2	9054.5	-	0	0.0
2009	15.2%	2	1121.4	-73.4%	1	0.3e^-1
2010	11.9%	11	164.2	16.5%	1	434.0
2011	15.2%	3	348.3	58.3%	1	0.8
2012	38.4%	10	193.8	-	0	0.0
2013	13.7%	7	205.7	7.9%	3	179.1
2014	22.0%	13	388.1	2.5%	8	478.4
2015	15.1%	13	375.6	5.6%	5	588.4
2016	11.0%	4	144.3	1.9%	4	687.8
2017**	19.0%	4	130.8	32.2%	1	324.4
Average and total	17.3%	94	485.1	9.6%	41	355.5

**European countries with a FinTech IPO within 2005-2017: Denmark, Finland, Germany, France, Luxembourg, Poland, Spain, Turkey, UK, Sweden.*
*** 2017 updated till 31/07/2017*

6.1.2 Cross-sectional regressions on the underpricing

In this section, several ex-ante uncertainty factors are regressed on the underpricing. These factors are variables which are tested as proxy for the ex-ante uncertainty of an IPO.

6.1.2.1 North-American companies

Table 6.3 reports the regression results. Firm age is significantly negative in every regression model, which is line with the theory discussed, preceding to hypothesis 1.4: "when a FinTech company is older, the level of underpricing is lower". The effect of firm age is as well economically significant, viewing the relative large size. Firm size, as measured by the market capitalization, has a positive effect, which is statistically significant in regression models 2, 3 and 4. The effect of the market capitalization is positive, which was not expected according to the literature. The Proceeds of an IPO have a, relatively small, negative effect on the underpricing, in regression models 2, 3 and 4, but appear to be not statistically significant, but the (negative) effect of the proceeds corresponds with the findings of Beatty and Ritter (1986). The positive effect of the dummy variable venture backed firm, contradicts hypothesis 1.7, but following the discussion, the effect could be positive by the effects of 'grandstanding'. Which is caused by unexperienced venture capitalists, who take companies public too early, this makes investors willing to pay less for the stock, resulting in a higher underpricing (Berlin, 1998).

Further, the positive effect of the underwriter's reputation corresponds with Beatty and Ritter (1986), who state that underwriters enforce the underpricing equilibrium, because they would be afraid to lose potential customers. Striking is that the effect of the dummy variable hot or cold market, is positive in regression model 2 and then changes in a negative effect in regression models 3 and 4. Therefore, it is hard to draw clear conclusions on the effect of a hot or cold market on the underpricing. In regression model 3, the variable number of uses of proceeds is added, showing an insignificant positive effect on the underpricing. The positive effect is in line with the discussed literature and hypothesis 1.5. As last, in regression model 4, aftermarket liquidity variables, standard deviation (of the stock on the aftermarket) and trading volume, are added. Standard deviation has a, statistically insignificant, positive effect on the underpricing. The trading volume has a small negative effect on the underpricing, which is statistically not significant. Viewing the decrease in adjusted R-squared of model 4 compared to model 3, the two added variables have few explanatory power.

The highest adjusted R-squared is 16.0% of regression model 5, and the lowest adjusted R-squared is of regression model 1. Therefore, regression model 5 seems to be the best model for explaining the North-American FinTech underpricing, following the F-statistic and adjusted R-squared. The F-statistic indicates the overall significance of all coefficients, compared to a model with only an intercept, so the higher the F-statistic the better the model. The root mean squared error (root MSE), is the standard deviation of the residuals. The residuals are a fit of the regression model with the data. The better the model fits the data, the lower is the Root MSE. The coefficients of model 5, of variables ln(age), ln(market cap) and venture backed firm, have a relatively large value, which indicates that these variables are economically significant. Venture backed firm is the most important variable, as it is strongly statistically significant and has the largest coefficient, which implies high economic significance as well.

Table 6.3: Overview of the regression models of US/Canadian underpricing

Variable	Model 1	2	3	4	5
Intercept	0.09 (0.47)	-0.01 (-0.07)	-0.03 (-0.16)	-0.04 (-0.19)	-0.32e-2 (-0.02)
Ln(age)	-0.09*** (-2.66)	-0.08** (-2.59)	-0.09*** (-2.67)	-0.09*** (-2.67)	-0.09*** (-2.78)
Ln (Market Cap)	0.02 (1.66)	0.03* (1.71)	0.02* (1.68)	0.03* (1.70)	0.02* (1.81)
Ln(Proceeds)		-0.02 (-0.54)	-0.01 (-0.44)	-0.01 (-0.29)	
Venture backed firm		0.18*** (3.05)	0.18*** (2.92)	0.17*** (2.87)	0.19*** (3.33)
Underwriter reputation		0.04 (0.40)	0.03 (0.30)	0.01 (0.13)	
Hot or cold IPO market		0.02 (0.18)	-0.01 (-0.13)	-0.02 (-0.22)	
Number uses of proceeds			0.01 (0.90)	0.01 (0.83)	
Standard deviation				0.01 (0.64)	
Trading volume				-1.80e-6 (-0.35)	
Adjusted R^2	**0.07**	**0.13**	**0.13**	**0.12**	**0.16**
F-statistic	**4.25**	**3.39**	**3.01**	**2.37**	**6.84**
Root MSE	**0.29**	**0.28**	**0.28**	**0.28**	**0.27**
#observations	**94**	**94**	**94**	**94**	**94**

As an indicator for multicollinearity between the variables, variance inflation factor (VIF) tests are done on each regression model, the outcomes of these tests are presented in appendix 1D. Higher levels of VIF, can influence the results of a multivariate regression analysis. A VIF test indicates the size of the effect on the standard errors of a specific beta weight that is caused by multicollinearity. Several maximum values for the VIF are recommended, in this thesis a maximum of 4 is taken, which is also done by Pan and Jackson (2008). When the VIF test produces a value of 4, this implies that the standard errors are 4 times larger than in a normal situation without inter-correlations between the predictor of interest and the other predictor variables of the multivariate regression analysis. As from the VIF tests presented in Appendix 1D appear, none of the regression models have multicollinearity problems.

6.1.2.2. The European companies

The same regression models as with the North-American companies are used for the European companies. Table 6.4, below, shows the results of the regressions of the variables on the underpricing.

Table 6.4: Overview of the regression models of European underpricing

	Model			
Variable	**1**	**2**	**3**	**4**
Intercept	0.39** (2.34)	0.35 (1.56)	0.36 (1.54)	0.43* (1.79)
Ln(age)	-0.19e^-2 (-0.05)	-0.01 (-0.29)	-0.01 (-0.27)	-0.02 (-0.50)
Ln (Market Cap)	-0.02 (-1.44)	0.02 (0.86)	0.02 (0.81)	0.01 (0.43)
Ln(Proceeds)		-0.05** (-2.21)	-0.05* (-2.07)	-0.04 (-1.46)
Venture backed firm		0.03 (0.43)	0.03 (0.42)	0.05 (0.51)
Underwriter reputation		-0.01 (-0.08)	-0.01 (-0.07)	0.01 (0.10)
Hot or cold IPO market		-0.22 (-1.57)	-0.22 (-1.50)	-0.25 (-1.69)
Number uses of proceeds			-0.32e^-2 (-0.16)	-0.49e^-2 (-0.24)
Standard deviation				0.28e^-2 (0.33)
Trading volume				5.07e^-6 (0.23)
Adjusted R^2	**0.02**	**0.14**	**0.11**	**0.02**
F-statistic	**1.41**	**2.05**	**1.70**	**1.06**
Root MSE	**0.19**	**0.18**	**0.18**	**0.18**
#observations	**39**	**39**	**39**	**37**

The constant term has positive coefficients in all the regression models, this is an important difference with the regression results of the North-American companies, where the constant term has negative values for models 2 till 5.

Again, firm age appears to have a negative effect on the underpricing. Difference with the North-American FinTechs, is that the effect is not statistically significant. Moreover, the size of the effect is relatively small, though the effect of age seems not economically significant. The effect of market capitalization is in regression model 1 negative, and in regression model 2, 3 and 4 positive, the effect is not statistically significant, and as the sign of the coefficient is changing, it is hard to draw conclusions on the precise effect of this factor on the underpricing of European FinTechs.

In regression model 2, four variables are added, among which are three dummy variables. The proceeds, similar as for the North-American FinTechs, have a significant negative effect on the underpricing. Viewing the size of the coefficients, the effect seems also economically significant, which corresponds with the North-American results. Further, it appears that venture backed companies have a positive relation with the underpricing, which corresponds with the effect of venture backed capital on the underpricing of the North-American FinTechs. Thus, the variable venture backed firm, again, provides evidence for the occurrence of 'grandstanding' with FinTech IPOs. When comparing the coefficients of venture backed firm for European and North-American FinTechs, the role of venture backed capital on underpricing seems to be more important in case of the North-American FinTechs.

The underwriter reputation has an insignificant negative effect in regression models 2 and 3 and the sign of the effect changes to positive in regression model 4. The dummy variable hot or cold IPO market, appears to have a, relatively large, negative effect on the underpricing. Which implies that in a hot market, the underpricing is lower. The effect is not statistically significant, but because the effect of a hot (or cold) market on the European FinTech underpricing is the largest, the effect can be considered as economically significant. The effect of a hot or cold market for the European FinTechs appears to be substantially larger than for the North-American FinTechs.

In regression model 3, the number of uses of proceeds is added as variable. This variable appears to have (such) a small negative effect on the underpricing, that it is not statistically, and economically, significant. Though, the sign of the effect corresponds with Beatty and Ritter (1986), who state that the number of uses of proceeds should have a negative relation with the underpricing, as a lower number of uses of proceeds would imply a lower ex-ante uncertainty. In regression model 4, the standard deviation of the stock and the trading volume are added. The standard deviation has a, statistically insignificant, positive effect, which implies that a less liquid stock has a higher underpricing. The effect of trading volume is not statistically and economically significant. A fifth regression with statistically significant variables is not performed, because there is only one significant variable. On the four regression models are VIF tests performed, which showed that there are no multicollinearity problems between the variables, as all the VIF statistics are below 4 (see Appendix 1D).

Regression model 2 shows the highest values of adjusted R-squared and F-statistic, and regression model 1 and 4 have the lowest values of adjusted R-squared and F-statistic. The low adjusted R-squared of regression model 4 is striking, because model 4 has the most variables of all used regression model, and even has seven variables more than model 2. So, regression model 2 seems to be the best model, for explaining the European FinTech underpricing.

6.1.2.3. All the companies

As last, the combined underpricing, caused by the European and the North-American FinTechs, is examined. Below table 6.5 reports the regression results.

Table 6.5: Overview regressions of US/Canada and Europe combined

Variable	**Model** **1**	**2**	**3**	**4**	**5**
Intercept	0.13 (0.95)	0.13 (0.88)	0.13 (0.84)	0.12 (0.77)	0.06 (0.49)
Ln(age)	-0.07*** (-2.64)	-0.06** (-2.52)	-0.06** (-2.59)	-0.07*** (-2.69)	-0.06** (-2.52)
Ln (Market Cap)	0.01 (1.37)	0.03** (2.11)	0.03** (2.10)	0.02* (1.93)	0.03** (2.30)
Ln(Proceeds)		-0.04** (-2.18)	-0.04** (-2.14)	-0.04* (-1.67)	-0.04** (-2.09)
Venture backed firm		0.14*** (2.96)	0.14*** (2.81)	0.15*** (2.93)	0.15*** (3.23)
Underwriter reputation		0.04 (0.64)	0.03 (0.48)	0.04 (0.55)	
Hot or cold IPO market		-0.05 (-0.69)	-0.07 (-0.89)	-0.07 (-0.91)	
Number uses of proceeds			0.01 (0.82)	0.01 (0.83)	
Standard deviation				0.13e^-2 (0.17)	

Trading volume				-7.99e^-7 (-0.18)	
Adjusted R^2	**0.03**	**0.12**	**0.12**	**0.11**	**0.13**
F-statistic	**3.16**	**4.10**	**3.60**	**2.84**	**5.96**
Root MSE	**0.27**	**0.26**	**0.26**	**0.26**	**0.26**
#observations	**133**	**133**	**133**	**131**	**133**

Similar as with the results in sections 6.1.2.1 and 6.1.2.2, age has a negative relation with the underpricing, which is statistically and economically significant. The market capitalization is positive in all the regression models, and is in regression models 2, 3 and 4 statistically significant. According to Schenone (2004) and Garfinkel (1993) firm size has a negative relation with ex-ante uncertainty, and thus should have a negative relation with underpricing. Proceeds has a statistically significant negative relation with underpricing, which is consistent with the regression results in paragraph 6.1.2.1 and 6.1.2.2.

The dummy variable venture backed firm, again, shows a statistically significant positive relation with the underpricing, overall, suggesting the occurrence of 'grandstanding' with FinTech companies. The dummy variable underwriter reputation has an insignificant positive effect on the underpricing, which is consistent with the results of the North-American companies. The variable hot or cold IPO market, appears to have a negative relation with the underpricing, which is consistent with the results of the European underpricing. In model 3, the number of uses of proceeds is added, this variable has a positive effect on the underpricing, which is not statistically significant. When the number of uses of proceeds increases with 1, the underpricing will increase with 0.01%, this effect is such a small effect that it is not economically significant. The size and sign of the number of uses of proceeds' coefficients are the same as the size of the coefficients of the North-American regression results. As last, the variables standard deviation and trading volume are added to the regression. Standard deviation has a small positive effect, which is statistically insignificant and trading volume has an even smaller negative effect, which is also statistically insignificant. The coefficients of both variables are so small, that they cannot be considered as economically significant. The signs of the coefficients of both variables are the same as those of the North-American companies.

In the regression model 5, the statistically significant variables are regressed on the underpricing. Firm age, again has a statistically and economically significant effect. Market capitalization has a statistically significant positive effect, but is, again, contradicting the expected effect of firm size on the underpricing. Proceeds has a similar effect as in the previous regressions, and is as well economically as statistically significant. Last variable is the dummy venture backed firm, which again has a significant positive effect. Regression model 5 has the highest explanatory power, implicated by the adjusted R-squared of 13.0% and F-statistic of 5.96. It seems that the variables standard deviation and trading volume, either have no or have very few explanatory power of the underpricing of the European and

North-American FinTech companies combined. And that the variable venture backed firm, and to a lesser extent age, are the most important variables, due to their statistical and economical significance.

VIF tests on the variables of the five regression models are performed, which showed that there are no multicollinearity problems between the variables (see Appendix 1D).

6.2. The long-term performance of FinTech companies

Past empirical research shows empirical evidence for the existence of the long-term IPO performance anomaly. Several FinTech companies are relatively new, therefore the long-term performance evaluation periods are one-year and three-year in this analysis, for longer evaluation periods more observations would be lost. The number of companies examined in the long-term, decreases over time, because several companies went bankrupt, were taken over, or relatively new companies (with an IPO in 2016 or 2017). For those reasons, 24 of the 96 North-American FinTechs and 10 of the European FinTechs are lost over the evaluation time. The companies that were listed, at least for a year, that the one-year performance could be measured, are used in the calculations of the (cumulative) abnormal returns.

On the long-term IPO performance of FinTechs hasn't been a lot of research done, so past empirical results on the FinTech IPO performance are not available, which makes it unable to compare the results with previous research.

Table 6.6 reports the long-term performance with the compounded buy-and-hold abnormal returns per period. Striking is that the North-American FinTechs have a positive long-term performance over both a one-year and a three-year period. On a one-year period after the IPO, the North-American companies have an average abnormal return of 4.31%, which is not statistically significant, and on the three-year period, the abnormal returns amount even 14.31%, which is also not statistically significant. The European FinTechs on the contrary have a large negative one-year post-IPO performance, with abnormal returns of -23.36%. The poor performance is strongly decreasing over time, implied by the small three-year abnormal returns of 0.16%. The results strongly suggest that the long-term performance of North-American FinTechs is better than that of the European FinTechs. When analyzing the abnormal returns of both companies together, the one-year abnormal returns have a negative value of -4.07%, not statistically significant, explained by the strong negative performance of the European firms, which will have a dominant effect on the abnormal returns. On the three-year period the long-term performance is positive with 10.15%, but is not statistically significant. But the statistical significance should be seen in perspective, as in comparison with the results of the short-term performance, the number of observations for the long-term performance is substantially smaller, the difference for North-America is 22 observations, and for Europe 10 observations.

Table 6.6: The compounded buy-and-hold abnormal returns

Calculated following Ikenberry, Lakonishok and Vermaelen (1995). These abnormal returns are calculated on a one-year and three-year period. The first two lines display the abnormal returns of all the FinTech companies in the dataset, with their own benchmarks. For calculating the ARs of the EU and US/Canada firms are, respectively, the STOXX Europe 600 Technology and the NASDAQ index used as benchmarks.

		Annual buy-and-hold returns			
	Year	n	Average AR (%)	t-statistic	Std. dev
All FinTechs	1	132	-4.07	-0.38	1.23
	3	102	10.15	1.08	0.95
European FinTechs	1	40	-23.36	-0.71	2.07
	3	30	0.16	0.01	0.81
US/Canada FinTechs	1	92	4.31	0.75	0.56
	3	72	14.31	1.21	1.00

The difference between table 6.6 and the following tables, is that table 6.6 displays buy-and-hold abnormal returns, where table 6.7 and 6.8 display firm adjusted returns. The difference is in rebalancing of the portfolios, when calculation the abnormal return, a more extensive explanation on the difference can be found in section 5 methodology.

On the next page, Table 6.7 displays the long-term performance of the US and Canadian FinTech companies. The abnormal returns (average adjusted returns) are calculated per month. Only 11 of the 36 monthly abnormal returns are negative, while the expectation was that the long-term performance would be poor. This unexpected performance is also reflected in the cumulative abnormal returns, which only counts three (insignificant) negative values. Furthermore, none of the abnormal returns values has an extremely high or low value, all of them are in the range of +0.20% and -0.20%. The cumulative abnormal return is the sum of the abnormal returns, over a specific period. And reflects the performance over several months, instead of over one month (abnormal return).

The number of firms declines over the months, because for some firms, it is not possible to measure the long-term performance. Reason is that some firms are taken over, went bankrupt, or did a recent IPO (in 2016 or 2017), so that the stock prices are not available over a year.

Overall seen, the low values of the ARs suggest that the FinTech companies are not underperforming the market, with the NASDAQ index as benchmark. This is strengthened by the positive CARs, which are 0.04% over a one-year period after the IPO, and 1.71% (significant on a 99% confidence level) over a three-year period.

The positive average CAR, three years post-IPO, is consistent with the positive average three-year buy-and-hold abnormal returns. The one-year buy-and-hold abnormal returns are lower than the three year buy-and-hold abnormal returns, similar is the one-year CAR smaller than the three-year CAR. Though, the comparison is between two different performance measures, it is a useful one, to monitor if both performance measures implicate a similar long-term performance.

Table 6.7: The average (cumulative) abnormal returns of the North-American firms

The average (cumulative) abnormal returns calculated 36 months after the IPO, in percent, with their corresponding t-statistics. Benchmark is the NASDAQ index. Seasoning month, indicates the month, after IPO, for which the AR and CAR are calculated.

Seasoning month	Number of firms	AR_t %	t-statistic	$CAR_{1,t}$ %	t-statistic
1	96	0.02	0.24		
2	96	0.20e^-2	0.03	0.10	0.17
3	96	0.08	0.91	0.95E^-4	0.67
4	95	-0.08	-1.01	0.12	0.05
5	95	0.12	1.72*	0.11	0.66
6	94	-0.03	-0.37	0.02	0.57
7	93	-0.05	-1.17	-0.03	0.11
8	93	0.12	-0.72	0.07	-0.11
9	92	-0.08	1.35	-0.01E^-2	0.33
10	92	0.14	-1.09	0.13	-0.05
11	92	-0.08	2.29**	0.05	0.52
12	92	-0.01	-1.07	0.04	0.19
13	92	0.03	-0.22	0.07	0.13
14	92	0.02	0.53	0.09	0.24
15	92	0.04	0.31	0.13	0.30
16	92	-0.10	0.65	0.18	0.42
17	92	0.04	0.60	0.12	0.60
18	90	-0.10	-1.16	0.18	0.37
19	89	0.03	0.43	0.12	0.53
20	88	0.07	1.10	0.17	0.69
21	88	0.11	1.53	0.23	1.01
22	88	0.05	0.79	0.35	1.14
23	88	0.18	1.46	0.40	1.59
24	88	0.02	0.27	0.58	1.63
25	86	0.06	0.78	0.60	1.55
26	84	-0.05	-0.82	0.68	1.67*
27	84	0.54e^-2	0.09	0.68	1.70*
28	84	0.15	2.04**	0.84	2.01**
29	84	0.11	1.30	0.94	2.36**
30	79	-0.07	-1.08	0.80	1.82*
31	77	-0.61e^-2	-0.11	0.70	1.55
32	75	0.07	0.53	0.81	1.80*
33	74	0.03	0.51	0.83	1.81*
34	74	0.07	0.83	0.89	2.06**
35	74	0.23	1.31	1.11	2.33**

36	72	0.39	1.47	1.71	3.46***

In table 6.8 below, the average abnormal returns of the European FinTech companies are reported. Only three of the 36 abnormal returns of the European companies are statistically significant, which is reflected by the low t-statistics. In 17 of the 36 months, there is a negative abnormal return, which is a larger amount than for the North-American companies. None of the abnormal returns have extremely high or low values, the highest AR is 0.25% for month 35 and the lowest AR is -0.10% for month 13. In the first month, the abnormal returns are negative, thereafter the ARs are positive. Several negative abnormal returns in a row are constantly followed by several positive abnormal returns in row, which are again alternated by several positive ARs in a row. The only freestanding negative ARs are for the first month and for the thirty-second month.

Table 6.8: The average (cumulative) abnormal returns of the European firms

The average (cumulative) abnormal returns calculated 36 months after the IPO, in percent, with their corresponding t-statistics. Benchmark is the STOXX Europe 600 Technology index. Seasoning month, indicates the month, after IPO, for which the AR and CAR are calculated.

Seasoning month	Number of firms	AR_t %	t-statistic	$CAR_{1,t}$ %	t-statistic
1	42	-0.07	-0.78		
2	42	0.19	1.95*	0.12	0.82
3	42	0.04	0.52	0.17	0.93
4	42	0.04	0.43	0.20	1.08
5	41	-0.33e^-2	-0.06	0.19	0.90
6	41	-0.08	-0.96	0.11	0.42
7	41	0.07	1.00	0.18	0.68
8	41	0.12e^-2	0.01	0.18	0.62
9	41	-0.08	-0.66	0.10	0.33
10	41	-0.14	-1.50	-0.04	-0.13
11	41	0.08	0.66	0.04	0.11
12	41	-0.09	0.78	0.13	0.32
13	40	-0.10	-0.92	0.04	0.10
14	40	-0.06	-0.35	-0.02	-0.05
15	40	-0.05	-0.52	-0.07	-0.17
16	39	-0.05	-0.47	-0.11	-0.24
17	39	-0.31	-1.82*	-0.42	-0.86
18	38	1.46e^-4	0.00	-0.31	-0.64
19	38	0.17	1.35	-0.14	-0.30
20	38	-0.05	-0.32	-0.20	-0.38
21	37	-0.05	-0.25	-0.18	-0.32
22	37	-0.02	-0.14	-0.20	-0.34
23	37	0.06	0.49	-0.13	-0.23
24	36	0.05	0.52	-0.14	-0.23
25	35	-0.06	-0.49	-0.24	-0.35
26	35	-0.09	-0.76	-0.33	-0.48

27	35	0.16	1.60	-0.17	-0.23
28	35	0.05	0.37	-0.12	-0.16
29	34	0.03	0.10	-0.13	-0.17
30	34	0.02	0.98	-0.11	-0.16
31	33	0.10	-0.54	0.03	0.04
32	33	-0.05	0.09	-0.02	-0.03
33	32	0.01	0.09	-0.03	-0.04
34	32	0.04	0.30	0.01	0.02
35	32	0.25	2.47**	0.27	0.33
36	32	0.09	1.04	0.36	0.44

Overall, the alternating positive and negative ARs do not suggest a poor long-term stock performance of the European FinTech companies after an IPO. The positive CAR over a one-year period of 0.13% and the CAR over a three-year period of 0.36%, indicate that the performance, though not statistically significant, indeed is not poor. The average CAR over one year is positive, whereas the average buy-and-hold abnormal return over a one-year period after the IPO is strongly negative, these results seem to be not consistent, though this difference can be caused by the difference in methodology of both calculations. Consistent with the CAR over the three-year period, the three-year average buy-and-hold abnormal return is also positive. The CAR (0.36%) is higher than the buy-and-hold abnormal return (0.16%).

Compared to the North-American FinTech companies, the cumulative abnormal returns measured over a one-year and a three-year period are both positive. The CARs of the European companies are not significant, which might be caused by the low number of European FinTechs with an IPO within the period 2005-2017.

6.2.1 Robustness on the long-term performance

Robustness checks for the long-term performance of the European and the North-American companies are done. In appendix 2A, the robustness checks of the North-American FinTechs are presented, as benchmark for the calculation of the average buy-and-hold abnormal returns and the (cumulative) adjusted returns, the New York ARCA Tech index is used. The results of the robustness checks are in line with the performance of the North-American FinTechs in the previous section, as the one-year and three-year BHARs and CARs are both positive. Therefore, the long-term performance of the North-American FinTech companies is good. Appendix 2B reports the results of robustness checks of the European FinTechs. Here, the MSCI Europe standard index is used as benchmark for the calculation of the average buy-and-hold abnormal returns and the (cumulative) adjusted returns of the European FinTechs. The one-year BHAR in Appendix 2B (9.60%) is not in line with the one-year BHAR in section 6.2 (-23.36%). Which implies that the long-term performance of European FinTechs is not poor, when measured against a non-tech benchmark.

CHAPTER 7 Conclusion

In this thesis, the post-IPO stock performance of North-American and European FinTech companies is examined. The corresponding research question was:

"What is the short- and long-term IPO performance of European and North-American (US and Canadian) FinTech companies".

To answer the research question, first, the short-term performance, measured by the underpricing, is examined, where after several variables, as proxies for ex ante uncertainty, are regressed on the underpricing, second, the long-term performance, measured by buy-and-hold abnormal returns and (cumulative) abnormal returns over one- and three-year periods after the IPO, are examined.

First, the short-term performance of FinTech IPOs, showed significant levels of underpricing of 17% for North-American and 10% European FinTech companies. The total level of underpricing of all examined FinTech companies, amounts 15% and is significant. Therefore, Hypothesis 1.1: "FinTech companies have a positive level of underpricing", is accepted. From a t-test appears that the underpricing of North-American FinTechs (17%) is significantly higher than the underpricing of their European peers (10%), consequently hypothesis 1.2: "The North-American FinTech companies have a higher level of underpricing than the European FinTech companies", is accepted. In comparison with the levels of underpricing of 14.0% for the US (2001-2016), and 6.5% (1971-2016), the North-American FinTech companies are more underpriced (17.0%) than other companies. And the European companies are not more underpriced (10.0%) than other European countries, like for instance Denmark 7.40% (1984-2011), Finland 16.70% (1971-2013), France 10.5% (1982-2010), Germany 23.00% (1978-2014) and Poland 12.70% (1991-2014).

Second, from the regression models can be concluded which ex ante uncertainty proxies (partly) explain the FinTech underpricing the best. First, the firm characteristics variables, firm age, has a negative effect on the underpricing, hypothesis 1.3, which is "When a FinTech company is older, the level of underpricing is lower", therefore must be accepted. Firm size, measured by market capitalization, appeared to have positive effects on the underpricing in the regressions with the underpricing of the North-American and all the firms, and a positive and negative effect with the underpricing of the European firms. According to Schenone (2004) and Garfinkel (1993), firm size should have a negative effect on the underpricing. That the effect of market capitalization is positive, can be due to market cap not measuring the firm size at the time of the IPO adequately, and so is not a good ex-ante uncertainty proxy. Hypothesis 1.4, "The underpricing is negatively correlated with the size of a FinTech company", therefore cannot be accepted. Further, hypothesis 1.5, “The higher the proceeds of an IPO, the lower the underpricing”, holds, as the effect of proceeds is negative in all regressions. The number of uses of proceeds has a positive relation with the underpricing in the regressions with underpricing of the North-American companies and all the companies, and a negative relation with the underpricing of the European companies. Therefore hypothesis 1.6: “The higher the number of uses of proceeds, the higher the underpricing” cannot be accepted for the European companies. As last, it appeared that a venture backed firm, has a higher underpricing than a non-venture backed firm, thereby hypothesis 1.7: “The underpricing of a venture capital backed firm’s IPO is lower than that of a non-venture capital backed firm”, does not hold. The coefficients of venture backed are significant in all the regression models, this implies that venture capital has an important role with the underpricing of FinTech IPOs. Furthermore, the results suggest that ‘grandstanding’ occurs in case of the FinTech companies.

Overall, from the regressions can be concluded that the underpricing is best explained by the firm age, market capitalization, proceeds and venture backed firms, as these variables have significant coefficients in the regressions. But the variable venture backed firm, appears to be the most important variable, because of its high, economical and statistical, significance in all the regressions.

As third, for the long-term performance the buy-and-hold abnormal returns and (cumulative) abnormal returns are calculated. Coming back to hypothesis 2.1, which is, “FinTech IPOs will underperform on the long-term (measured over one-year and three-year periods)”. The North-American FinTech companies have positive buy-and-hold and cumulative abnormal returns over the one-year and three-year period. So, the North-American FinTechs outperform on the long-term. The European FinTechs have negative buy-and-hold abnormal returns, but positive cumulative abnormal returns, over the one-year period, and slightly positive buy-and-hold abnormal returns over the three-year period. Therefore, the European FinTechs underperform on a one-year period. Though, the long-term performance of the European FinTech is contradicted by a robustness check, with a different (non-tech) benchmark.

Overall, the performance of the FinTech companies becomes over the years more positive, which is striking, and in contrast with previous findings of among many others Ritter (1991), Loughran and Ritter (1995) and Ritter and Welch (2002).

7.1 Limitations and recommendations for future research

An important limitation is that the performance of the FinTech companies in the dataset isn’t compared with comparable (non-FinTech) companies with a propensity matching score. Further, this thesis aims only at the North-American and European FinTech companies with an IPO within 2005-2017, the number of observations could be bigger when taking all FinTech companies worldwide or selecting a bigger time interval. Still, with FinTech IPOs being a relatively recent phenomenon, the sample size of this thesis is relatively small compared to other IPO studies. Especially for the long-term analysis, where several recent IPOs are lost.

Another limitation is the way the underwriter reputation is measured, with a dummy variable, instead of with a ranking score. Also, it might be better to measure the firm size with the total assets, instead of the market capitalization, but the data of total assets was not available for all the companies in Thomson-One, therefore the market capitalization is selected as firm size. Besides several more variables could be used as ex-ante uncertainty proxy, for instance the number of underwriters, the beta of a stock or the total assets.

When doing future research, it is recommendable to examine the IPO performance of FinTech companies worldwide, instead of only Europe and North-America, thereby keeping the regions separated to be able to compare between continents. Besides, a contributable addition to this research, would be to make a comparison of the short- and long-term FinTech performance with the performance of comparable (non-FinTech) companies, with a propensity matching score.

The performance of companies of specific verticals within the FinTech industry could provide interesting insights, the blockchain and cryptocurrencies vertical, for instance, is very hot at this moment. Further, the effect of cooperation and mergers and acquisitions between non-FinTechs with FinTech firms can be analyzed.

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APPENDIX

Appendix 1A: Overview of US/Canadian FinTechs

Issuer	IPO date	Offer Price	Closing_ price 1st day	Age	Marketcap	Proceeds ($ mil)	Lead manager	Underwriter_reputation	#use_of_proceeds	Venture Backed	St.Dev	Turnover by value
Amber Road Inc	21-3-2014	13,00	17	30,22	224020	96,09	Stifel	1	6	Yes	0,757602	161,6622
Apigee Corp	24-4-2015	17,00	16,7	10,89	537070	86,96	Morgan Stanley/ J.P.	1	5	Yes	0,916486	243,4555
AppFolio Inc	26-6-2015	12,00	14,08	9,48	397500	74,40	Morgan Stanley/ Cred	1	5	Yes	1,284375	107,0937
Bankrate Inc	17-6-2011	15,00	15,34	35,46	1.246.770	300,00	Goldman, Sachs/ Bof.	1	4	No	0,804735	384,8391
BATS Global Markets Inc	15-4-2016	19,00	23	10,87	3386300	147,41	Morgan Stanley/ Citig	1	4	No	1,0885	475,1672
Black Knight Financial Svcs	20-5-2015	24,50	27,11	0,56	3.039.240	441,00	J.P. Morgan/ BofA Me	1	2	No	0,478637	441,6773
Blackhawk Network Holdings Inc	19-4-2013	23,00	26,01	12,30	2332060	230,00	Goldman, Sachs/ Bof.	1	1	No	0,833081	275,9047
Bofl Holding Inc	15-3-2005	11,50	11,5	5,69	1482070	35,10	W.R. Hambrecht	0	4	No	0,048095	106,2421
Cachet Financial Solutions Inc	9-7-2014	1,50	33,75	4,43	10.340	6,75	Northland Capital Mar	0	7	No	0,702467	0,748246
Cardtronics Inc	11-12-2007	10,00	9,5	18,94	1524750	120,00	Deutsche Bank/Willia	1	2	No	0,286266	209,344
Carolina National Corp	15-12-2005	16,00	17	5,96	45380	16,00	Scott & Stringfellow	0	6	No	0,27531	4,33211
CBOE Holdings Inc	15-6-2010	29,00	32,49	37,45	10041260	339,30	Goldman Sachs	1	3	No	1,723104	586,2227
CBOT Holdings Inc	19-10-2005	54,00	14,96	157,80	12021100	172,34	Credit Suisse First Bo	1	6	No	11,80278	532,4768
ChannelAdvisor Corp	23-5-2013	14,00	18,44	11,98	305430	80,50	Goldman, Sachs/ Stif	1	4	Yes	0,989726	266,2797
Cotiviti Holdings Inc	26-5-2016	19,00	17,11	3,98	3406280	237,50	Goldman Sachs/ J.P.	1	3	No	0,664058	416,5787
Cowen Group Inc	13-7-2006	16,00	15,88	88,53	438690	179,48	Cowen/Credit Suisse/	1	2	No	0,457336	215,9992
CPI Card Group Inc	9-10-2015	10,00	12,17	33,77	127860	150,00	BMO Capital Markets	1	3	No	0,743752	411,7696
Currency Exchange Intl Corp	9-3-2012	6,65	7,25	13,92	154950	8,06	Jones, Gable & Comp	0	5	No	0	4,557143
Demandware Inc	15-3-2012	16,00	23,59	8,20	2850490	88,00	Goldman, Sachs/ Deu	1	3	Yes	1,884799	229,6961
Dollar Financial Corp	28-1-2005	16,00	10,67	26,08	367420	120,00	Piper Jaffray/Jefferies	1	4	No	0,214844	277,7402
Elevate Credit Inc	6-4-2017	6,50	7,76	3,18	341470	80,60	UBS Securities/ Jeffe	1	3	Yes	0,337122	216,8017
Ellie Mae Inc	15-4-2011	6,00	6,77	13,62	3832110	45,00	Barclays Capital	1	7	Yes	0,200669	94,02835
Emdeon Inc	12-8-2009	15,50	16,52	3,61	1731030	367,35	Morgan Stanley	1	1	No	0,31228	625,6032
Envestnet Inc	29-7-2010	9,00	10,23	11,57	1707100	63,00	Morgan Stanley/UBS	1	4	Yes	0,137362	101,6024
Equity Bancshares Inc	11-11-2015	22,50	23,89	12,86	383360	43,65	Keefe, Bruyette & Wo	0	5	Yes	0,132411	37,192
ESI Ent Sys Inc	30-3-2006	3,00	3,05	15,24	1570	8,82	Desjardins Securities	0	1	Yes	0,365079	11,67593
EverBank Financial Corp	3-5-2012	10,00	10,6	8,23	2492380	192,20	Goldman, Sachs/ Bof.	1	3	No	0,230683	352,473
Evertec Inc	12-4-2013	20,00	20,44	9,03	1233680	505,26	Goldman, Sachs/ J.P.	1	2	No	0,317067	692,0961
Fifth St Asset Mgmt Inc	30-10-2014	17,00	13,37	0,48	54520	102,00	Morgan Stanley/ J.P.	1	1	No	0,482117	157,0416
Financial Engines Inc	16-3-2010	12,00	17,25	13,84	2442450	127,20	Goldman Sachs	1	4	Yes	0,580867	235,1913
First Data Corp	15-10-2015	16,00	15,75	26,78	6912650	2.560,00	Citigroup/ Morgan Sta	1	3	No	0,7428	4406,602
FleetCor Technologies Inc	15-12-2010	23,00	27,25	10,31	13242700	291,53	J.P. Morgan/ Goldmai	1	4	Yes	1,232043	214,0032
FX Alliance Inc	9-2-2012	12,00	13,74	5,44	626450	62,40	BofA Merrill Lynch/ G	1	1	Yes	0,23827	119,8126
FXCM Inc	2-12-2010	14,00	14,85	11,92	10490	210,84	Credit Suisse/ J.P. M	1	3	No	8,524145	46,84048
GAIN Capital Holdings Inc	15-12-2010	9,00	8,85	11,12	278930	81,00	Morgan Stanley/Deuts	1	1	Yes	0,550676	144,2548
Genpact Ltd	2-8-2007	14,00	16,75	10,58	5252260	494,12	Morgan Stanley/Citi/J	1	6	No	0,917809	456,2333
GFI Group Inc	26-1-2005	21,00	26,44	18,07	1050510	123,00	Citigroup/Merrill Lynch	1	6	No	0,12053	687,6173
Global Cash Access Hldg Inc	23-9-2005	14,00	14,96	7,73	491.540	224,90	Goldman Sachs/JP M	1	6	No	0,307689	271,5968
Green Dot Corp	22-7-2010	36,00	43,99	10,72	1972610	164,09	J.P. Morgan/Morgan S	1	1	Yes	1,359052	227,3276
Groupon Inc	4-11-2011	20,00	26,11	3,01	2435320	700,00	Morgan Stanley/ Gold	1	1	Yes	3,895369	2921,486
Guidewire Software Inc	25-1-2012	13,00	17,12	11,06	5031710	115,05	J.P. Morgan/ Deutsch	1	5	Yes	2,021228	377,4197
Hamilton Lane Inc	1-3-2017	16,00	18,02	26,16		190,00	J.P. Morgan/ Morgan	1	3	No	0,362103	238,2625
HealthEquity Inc	31-7-2014	14,00	17,6	11,87	3079070	127,40	J.P. Morgan/ Wells Fa	1	6	No	1,481573	211,0833
Heartland Payment Systems Inc	11-8-2005	18,00	24,51	8,07	3813990	121,50	Citigroup	1	5	Yes	0,875653	156,1865
Higher One Holdings Inc	17-6-2010	12,00	14,27	10,46	250620	108,00	Goldman Sachs	1	3	No	0,210928	184,2938
Interactive Brokers Group Inc	4-5-2007	30,01	31,3	30,34	2497880	1.200,40	Not Applicable/ WR Hambrecht & Co LLC/ HSBC/	0	2	No	1,250075	964,6586
IntercontinentalExchange Inc	16-11-2005	26,00	39,25	5,52		415,94	Morgan Stanley/Goldr	1	5	Yes	0,332266	6093,687
International Sec Exchange Inc	9-3-2005	18,00	30,4	8,18	2618750	180,89	Bear Stearns/Morgan	1	4	No	1,646097	441,8535
JGWPT Holdings Inc	8-11-2013	14,00	12,82	0,38	2.690	136,50	Barclays/ Credit Suiss	1	2	No	1,311204	240,2176
LendingClub Corp	11-12-2014	15,00	23,43	8,11	2334310	870,00	Morgan Stanley/ Gold	1	8	Yes	1,294666	3539,279
Liquid Holdings Group Inc	26-7-2013	9,00	7,64	2,57	80	28,58	Sandler ONeill & Part	0	5	No	0,402284	16,66048
Liquidity Services Inc	23-2-2006	10,00	12,29	7,15	176640	76,87	Friedman Billings Ran	0	6	Yes	0,381762	270,5469
MasterCard Inc	25-5-2006	39,00	4,6	40,39	1,3E+08	2.399,32	Goldman Sachs/Citigi	1	4	No	0,152899	25829,74
MINDBODY Inc	19-6-2015	14,00	11,56	17,46	1116540	100,10	Morgan Stanley/ Cred	1	6	No	0,705514	294,2664
Mogo Finance Technology Inc	25-6-2015	10,00	9,48	11,83	74110	40,91	BMO Nesbitt Burns	1	4	No	0,869579	46,10236
Morningstar Inc	3-5-2005	18,50	20,05	21,34	3344720	140,83	W.R. Hambrecht	0	1	Yes	0,795537	138,8922
MSCI Inc	15-11-2007	18,00	24,97	9,37	9609850	252,00	Morgan Stanley	1	2	No	1,335783	375,7808
NantHealth Inc	2-6-2016	14,00	18,59	5,91	-	91,00	Jefferies/ Cowen and (	1	1	Yes	1,672064	159,1289
National Commerce Corp	19-3-2015	19,50	21,12	8,30	542440	33,15	Keefe, Bruyette & Wo	0	4	No	0,296181	25,65748
Nationstar Mortgage Hldg Inc	8-3-2012	14,00	14,2	18,18	1785330	233,33	BofA Merrill Lynch/Cit	1	3	No	0,325487	746,089
NetSpend Holdings Inc	19-10-2010	11,00	13	11,27	880080	203,90	Goldman, Sachs/ Bof.	1	5	No	0,922839	409,1394
NewStar Financial Inc	14-12-2006	17,00	17,71	2,54	448080	204,00	Goldman Sachs/Morg	1	3	Yes	0,212797	290,1129
Northern Aspect Resources Ltd	17-1-2012	0,20	0,35	0,76		0,20	Macquarie Private We	0	1	No	0,102598	12,15
NYMEX Holdings Inc	17-11-2006	59,00	132,99	0,00	7692200	383,50	JPMorgan/Merrill Lync	1	7	No	5,263147	1120,56
On Deck Capital Inc	17-12-2014	20,00	27,98	7,96	310230	200,00	Morgan Stanley/ BofA	1	5	Yes	1,831348	570,836
optionsXpress Holdings Inc	27-1-2005	16,50	20,3	4,99	724940	198,00	Goldman Sachs/Merri	1	5	No	1,004004	368,3732
Paycom Software Inc	15-4-2014	15,00	15,35	0,45	4209820	99,68	Barclays/ J.P. Morgan	1	7	No	0,560563	154,1898
Paylocity Holding Corp	19-3-2014	17,00	24,04	16,80	2467860	119,77	Deutsche Bank Secur	1	8	Yes	2,408717	281,7543
Penson Worldwide Inc	17-5-2006	17,00	19,5	11,37	120	126,92	JPMorgan/Credit Suis	1	6	Yes	0,658074	165,8422
Planet Group Inc	17-3-2006	1,25	125	7,21	80290	12,29	Canaccord Adams	0	1	Yes	12,90479	30,19643
Q2 Holdings Inc	20-3-2014	13,00	15,17	9,05	1578630	100,89	J.P. Morgan/ Stifel	1	7	Yes	1,160537	277,8142
Real Matters Inc	11-5-2017	13,00	12,89	12,56	776540	114,00	BMO Nesbitt Burns Inc/ INFOR	0	1	Yes	0,286824	93,54891
Redfin Corp	28-7-2017	15,00	21,7	13,57	2186860	138,47	Goldman Sachs/ Aller	1	3	Yes	1,844706	1743,223
Refco Inc	11-8-2005	22,00	27,48	36,19	15300	583,00	Credit Suisse First Bo	1	6	No	1,044588	1596,067
RiskMetrics Group Inc	25-1-2008	17,50	23,75	14,06	1501530	245,00	Credit Suisse/Goldma	1	1	Yes	0,691242	336,0016
SciQuest Inc	24-9-2010	9,50	12,27	14,82	493460	57,00	Stifel Nicolaus Weisel	0	5	No	0,448405	61,15748
Shopify Inc	21-5-2015	17,00	31,25	10,64	7696000	130,90	Morgan Stanley/ Cred	1	8	Yes	4,599629	40,76929
Springleaf Holdings Inc	16-10-2013	17,00	19,26	0,20	3750570	357,77	BofA Merrill Lynch/ Ba	1	1	No	0,806856	507,8905
Square 1 Financial Inc	27-3-2014	18,00	20,6	9,40	787320	104,06	Sandler ONeill & Part	0	4	No	0,547238	163,9913

Square Inc	19-11-2015	9,00	13,07	6,39	11040000	243,00	Goldman Sachs/ Morg	1	5	Yes	0,319366	2929,675
SS&C Technologies Hold	31-3-2010	15,00	7,54	14,67	7917560	160,88	J.P. Morgan	1	5	No	0,320401	424,2134
Synchrony Financial	07-31-2014	23,00	23	10,88	23319230	2.875,00	Goldman Sachs/ J.P.	1	1	No	1,063183	2009,778
TransUnion	25-6-2015	22,50	25,4	3,36	7943570	664,77	Goldman Sachs & Co/ JP Morgan & Co Inc/ Merrill Lynch/ Pierce Fenner &	1	1	No	0,287682	664,7914
TriNet Group Inc	27-3-2014	16,00	25,74	26,23	2349400	240,00	J.P. Morgan/ Morgan	1	1	No	0,217911	785,1422
Trulia Inc	20-9-2012	17,00	32,8	7,05	1828280	102,00	J.P. Morgan/ Deutsch	1	4	Yes	1,582438	1627,556
Vantiv Inc	22-3-2012	17,00	22,47	42,22	9906580	500,00	J.P. Morgan/ Morgan	1	4	No	0,665684	755,4677
VeriFone Holdings Inc	29-4-2005	10,00	10,75	24,32	1941470	154,00	JP Morgan/Lehman B	1	5	No	0,736423	302,3766
Verisk Analytics Inc	7-10-2009	22,00	27,22	38,77	13852180	1.875,50	BofA Merrill Lynch/Mc	1	1	No	0,689861	1437,661
Veritex Holdings Inc	9-10-2014	13,00	13,95	5,27	417440	35,10	Sandler ONeill + Partı	0	3	No	0,356655	21,8624
Virtu Financial Inc	16-4-2015	19,00	22,18	1,49	699480	314,11	Goldman Sachs/ J.P.	1	6	No	0,524661	570,5141
Virtusa Corp	3-8-2007	14,00	11,86	10,75	901780	61,60	JPMorgan	1	7	Yes	0,85604	63,22778
Visa Inc	19-3-2008	44,00	56,5	38,21	1,75E+08	17.864,00	JPMorgan/ Goldman S	1	3	No	0,637266	61133,61
Workday Inc	12-10-2012	28,00	48,69	7,62	13127520	637,00	Morgan Stanley/ Gold	1	3	Yes	2,569824	864,2862
Xoom Corp	15-2-2013	16,00	25,49	12,12	986590	101,20	Barclays/ Needham	1	4	Yes	1,524945	226,0732
Yintech Invest Hldg Ltd	27-4-2016	13,50	13,5	0,48	688770	101,25	Jefferies	1	1	No	0,337181	88,79453
Yodlee Inc	3-10-2014	12,00	13,44	15,59	536330	75,00	Goldman Sachs/ Cred	1	6	Yes	1,130233	297,5864

Appendix 1B: Overview of the European FinTechs

Issuer	**Offer Price**	**1st day closing price**	**Market Cap**	**Age**	**Proceeds**	**Venture Backed**	**#useproceeds**	**Lead manager**	**Underwriter Reputation**	**Turnover by volume**	**St.Dev**
Alfa Finl Software Hldg PLC	325	429,75	1.461.600	27,72	324,35	1	0	Barclays Bank PLC/Numis	1	676,2735	8,83042
Bango Limited	134	133,94	159.480	5,75	20,03	0	2	Panmure Gordon & Co Ltd	0	91,15128	14,85036
Bolsas y Mercados Espanoles	31	29,75	2.408.130	4,41	989,45	0	1	BBVA Securities/BNP Paril	0	412,4992	0,670108
Brightside Group PLC	69	69	122.970	0,30	27,17	0	1	Teather & Greenwood Ltd	0	18,82286	6,472818
CMC Markets PLC	240	240	439.360	11,67	315,41	0	1	Morgan Stanley & Co. Inter	1	819,5472	6,31956
Collector AB	55	60,37	9.216.470	16,44	120,62	0	2	SEB	0	125,9631	2,000938
eCard SA	2	18,64	41.680	6,31	4,40	0	2	UniCredit	0	49,21746	1,792304
eFront SA	6	6,4	55.150	7,95	500,00	1	2	Invest Securities	0	6,91157	0,45228
Equiniti Group PLC	165	165	877.220	5,91	484,89	0	7	Goldman Sachs & CoBarcla	1	1573,203	7,224445
EuroInvestor.com A/S	10,5	16,5	205.580	10,45	3,19	0	1	Not Available	0		1,779858
Euronext NV	20	20	3.598.700	163,47	1.127,86	0	1	Goldman Sachs & CoINGM	1	228,2992	0,352807
Experian Group Ltd	560	560	13.718.270	10,77	1.496,00	0	1	Merrill Lynch International L	1	8632,517	7,955261
FAIRFX Group plc	45	44,86	69.050	0,42	4,35	0	1	Cenkos Securities PLC	0	39,00354	3,27303
Ferratum Oyj	17	17	541.030	10,10	109,21	0	4	ICF Kursmakler AG	0	2,757258	0,526232
Financial Payment Systems Ltd	12	12	370	1,45	9,26	0	1	Daniel Stewart Securities P	0	158,3684	0,499342
Fireone Group PLC	241	241	30.420	0,14	43,74	0	2	Numis Securities Ltd	0	173,0594	8,311533
Gielda Papierow Wartosciowych	46	54	1.918.120	19,55	433,96	0	1	CitigroupJP Morgan Securit	1	155,4	1,137685
GlobeOp Financial Services SA	230	237,5	791.650	7,58	96,47	1	1	Merrill Lynch & Co Inc	1		3,435017
Idea Bank SA	24	26,39	279.600	24,32	67,34	0	1	Goldman Sachs & CoBank	1	9,822047	0,626303
Luxoft Holding Inc	17	20,38	1.042.590	13,23	69,57	1	3	UBS Securities IncCredit S	1	89,4874	0,540558
Markit Ltd	24	26,7	18.941.910	0,42	1.283,34	0	3	Bank of America Merrill Lyn	1	776,8281	0,314038
Meilleurtaux SA	13,7	13,7	47.800	5,67	58,74	0	1	Not Available/Gilbert Dupon	0	3,618898	0,613647
Merkez B Tipi Menkul Kiymetler	1	1,03	76.500		2,41	0	2	Not Available	0	247,1656	0,053123
Mobile Credit Baltic Plc	150	150	21.850	0,08	7,34	0	1	Not Available	0	25,79231	2,325347
Monitise PLC	0,22	22	71.620	3,49	42,71	0	1	Investec Bank (UK) Ltd	0	1144,602	1,341334
MyBucks SA	13,5	13,5	154.620	5,48	15,19	0	1	Hauck & Aufhaeuser Corpo	0	0,358	0,619259
Nektan plc	236	236	9.550	3,84	5,82	1	3	Panmure Gordon (UK) Ltd	0	12,3439	13,96544
Nets A/S	150	145	30.282.110	48,73	2.371,81	1	4	Deutsche Bank/Morgan Sta	1	867,3246	7,062017
NWAI Dom Maklerski SA	12	19	4.090	9,23	0,78	0	1	Not Applicable	0	0,085047	1,109576
QIWI PLC	17	17,08	788.460	6,18	212,50	0	3	JP Morgan & Co Inc/Credit	1	346,8492	0,452435
Rentabiliweb Group SA	3	3	152.990	4,93	51,30	0	2	Not Available	0	5,869355	0,163791
Rosslyn Data Tech PLC	33	31,19	11.990	9,32	17,24	0	7	Cenkos Securities PLC	0	98,95146	0,927546
SafeCharge Intl Group Ltd	162	169,5	380.790	8,25	126,06	0	3	Shore Capital & Corporate I	0	323,0707	1,255514
Travelport Worldwide Ltd	16	16,4	1.921.620	8,73	480,00	0	5	Morgan Stanley & Co/UBS	1	616,0175	1,406436
Tungsten Corp PLC	225	225	79.420	13,79	255,22	0	4	Charles Stanley Securities(	0	666,1688	12,10172
West International AB	7	5,81	281.250	19,82	3,14	0	1	Not Available	0	12,84216	0,455464
Woogroup SA	12,73	3,18	46.780		0,03	0	1	Europe Finance et Industrie	0	0,175	0,310532
Worldline SA	16	16,03	4.698.840	23,91	782,29	0	2	Societe Generale SABank (	1	59,76047	0,200707
Worldpay Group PLC	240	240	6.460.000	26,79	2.160,00	0	5	Barclays & Credit Suisse &	1	6714,027	9,622436
Xchanging PLC	240	240	480.270	8,31	404,44	1	2	Citigroup Global Markets Lt	1	1442,952	12,97832
X-Trade Brokers SA	11,5	12	639.740	14,35	48,81	0	2	JP Morgan & Co IncPekao (	1	67,69141	1,084787

Appendix 1C: T-test on difference in underpricing between North-American FinTechs and European FinTechs.

```
. ttest Underpricing_NA == Underpricing_EU, unpaired

Two-sample t test with equal variances
------------------------------------------------------------------------------
Variable |     Obs        Mean    Std. Err.   Std. Dev.   [95% Conf. Interval]
---------+--------------------------------------------------------------------
Underp~A |      94    .1733737    .0309166    .2997476    .1119795     .234768
Underp~U |      41    .0958355    .0364261    .2332406    .0222157    .1694553
---------+--------------------------------------------------------------------
combined |     135    .1498251    .0243246    .2826263    .1017152    .1979349
---------+--------------------------------------------------------------------
    diff |            .0775383    .0526672               -.0266354    .1817119
------------------------------------------------------------------------------
    diff = mean(Underpricing_NA) - mean(Underpricing_EU)          t =   1.4722
Ho: diff = 0                                     degrees of freedom =      133

    Ha: diff < 0                 Ha: diff != 0                 Ha: diff > 0
 Pr(T < t) = 0.9283         Pr(|T| > |t|) = 0.1433          Pr(T > t) = 0.0717
```

Appendix 1D: VIF tests for multicollinearity on the regression models

Regressions of the North-American companies:

VIF regression model 1:

```
. vif

    Variable |       VIF       1/VIF
-------------+----------------------
ln_marketcap |      1.04    0.965120
       lnage |      1.04    0.965120
-------------+----------------------
    Mean VIF |      1.04
```

VIF regression model 2:

```
. vif

    Variable |       VIF       1/VIF
-------------+----------------------
 ln_proceeds |      1.85    0.541076
ln_marketcap |      1.44    0.695214
Underwrite~n |      1.37    0.730337
       lnage |      1.08    0.927591
VentureBac~d |      1.06    0.942495
   HotorCold |      1.04    0.965042
-------------+----------------------
    Mean VIF |      1.31
```

VIF test regression model 3:
. vif

Variable	VIF	1/VIF
ln_proceeds	1.85	0.541076
ln_marketcap	1.44	0.695214
Underwrite~n	1.37	0.730337
lnage	1.08	0.927591
VentureBac~d	1.06	0.942495
HotorCold	1.04	0.965042
Mean VIF	1.31	

VIF regression model 4:
. vif

Variable	VIF	1/VIF
ln_proceeds	2.16	0.463165
ln_marketcap	1.46	0.686094
Underwrite~n	1.45	0.690529
Turnoverby~e	1.43	0.699436
lnage	1.11	0.903167
StDev	1.08	0.926489
HotorCold	1.08	0.927412
VentureBac~d	1.06	0.941466
Mean VIF	1.35	

VIF test regression model 5:
. vif

Variable	VIF	1/VIF
ln_marketcap	1.04	0.964816
lnage	1.04	0.965030
VentureBac~d	1.00	0.999511
Mean VIF	1.02	

Regressions of the European companies:

VIF test regression model 1:
. vif

Variable	VIF	1/VIF
ln_marketcap	1.30	0.767473
lnage	1.30	0.767473
Mean VIF	1.30	

VIF test regression model 2:

```
. vif
```

Variable	VIF	1/VIF
ln_marketcap	3.01	0.332534
ln_proceeds	2.83	0.352760
Underwrite~n	2.28	0.438593
lnage	1.44	0.693247
VentureBac~d	1.14	0.880598
HotorcoldM~t	1.13	0.881569
Mean VIF	1.97	

VIF test regression model 3:

```
. vif
```

Variable	VIF	1/VIF
ln_marketcap	3.08	0.324932
ln_proceeds	3.01	0.332598
Underwrite~n	2.29	0.437442
lnage	1.45	0.688057
HotorcoldM~t	1.17	0.857736
useproceeds	1.16	0.863542
VentureBac~d	1.14	0.880438
Mean VIF	1.90	

VIF test regression model 4:

```
. vif
```

Variable	VIF	1/VIF
ln_proceeds	3.35	0.298137
ln_marketcap	3.26	0.306383
Underwrite~n	2.29	0.437370
Turnoverby~e	1.58	0.634443
lnage	1.51	0.660254
StDev	1.46	0.684423
VentureBac~d	1.37	0.731221
HotorcoldM~t	1.18	0.844466
useproceeds	1.18	0.847131
Mean VIF	1.91	

Regressions of the European and North-American companies combined:

VIF test regression model 1:

```
. vif
```

Variable	VIF	1/VIF
ln_marketcap	1.10	0.913155
lnage	1.10	0.913155
Mean VIF	1.10	

VIF test regression model 2:

```
. vif
```

Variable	VIF	1/VIF
ln_proceeds	2.08	0.481803
ln_marketcap	1.75	0.570351
Underwrite~n	1.66	0.600970
lnage	1.13	0.882773
VentureBac~d	1.07	0.936272
HotorCold	1.01	0.987189
Mean VIF	1.45	

VIF test regression model 3:

```
. vif
```

Variable	VIF	1/VIF
ln_proceeds	2.08	0.481005
ln_marketcap	1.75	0.570267
Underwrite~n	1.73	0.579557
use_of_pro~s	1.18	0.845549
lnage	1.14	0.874189
HotorCold	1.10	0.910608
VentureBac~d	1.09	0.915507
Mean VIF	1.44	

VIF test regression model 4:

```
. vif
```

Variable	VIF	1/VIF
ln_proceeds	2.32	0.430675
ln_marketcap	1.80	0.554216
Underwrite~n	1.77	0.564526
Turnoverby~e	1.29	0.772382
use_of_pro~s	1.20	0.832722
HotorCold	1.17	0.852054
lnage	1.15	0.866652
VentureBac~d	1.10	0.906919
StDev	1.04	0.959992
Mean VIF	1.43	

VIF test regression model 5:

```
. vif

    Variable |       VIF       1/VIF
-------------+----------------------
 ln_proceeds |      1.72    0.581551
ln_marketcap |      1.70    0.588249
       lnage |      1.13    0.883741
VentureBac~d |      1.01    0.991111
-------------+----------------------
    Mean VIF |      1.39
```

Appendix 2A: Robustness check on the LT-performance of North-American companies

Table 8.1: The buy-and-hold abnormal returns are calculated with the NYSE ARCA Tech as benchmark.

		Annual buy-and-hold returns		
	Year	n	Average AR (%)	t-statistic
US/Canada	1	92	2.79	0.48
	3	72	7.91	0.67

Table 8.2: The average abnormal returns (AR_t) and the cumulative average returns (CAR_t) with the NYSE ARCA Tech Index as benchmark.

Seasoning month	Number of firms	AR_t %	t-statistic	$CAR_{1,t}$ %	t-statistic
1	96	0.02	0.34		
2	96	-0.02	-0.32	0.19E^-2	0.02
3	96	0.08	0.88	0.08	0.53
4	95	-0.04	-0.46	0.04	0.18
5	95	0.09	1.27	0.12	0.63
6	94	-0.03	-0.47	0.10	0.53
7	93	-0.15	-1.80*	-0.03	-0.13
8	93	0.03	0.43	-0.14e^-2	-0.01
9	92	0.07	0.94	0.07	0.31
10	92	-0.05	-0.73	0.01	0.05
11	92	0.05	0.67	0.06	0.25
12	92	-0.03	-0.57	0.03	0.11
13	92	-0.04	-0.48	-0.64e^-2	-0.02
14	92	0.12	1.54	0.12	0.40
15	92	-0.02	-0.36	0.09	0.29
16	92	0.07	0.77	0.16	0.54
17	91	-0.07	-0.86	0.15	0.49
18	90	0.11	1.58	0.24	0.74
19	88	0.08	-0.09	0.25	0.75
20	88	0.08	1.39	0.36	1.06

21	88	0.05	1.26	0.44	1.25
22	88	0.06	0.72	0.52	1.46
23	88	0.05	0.83	0.57	1.59
24	86	0.07	0.85	0.61	1.58
25	84	-0.06	-0.90	0.69	1.74*
26	84	-0.02	-0.37	0.67	1.69*
27	84	0.20	2.65***	0.87	2.21**
28	84	0.03	0.38	0.89	2.18**
29	79	-0.03	-0.62	0.78	1.80*
30	77	-0.05	-0.82	0.65	1.43
31	75	0.12	1.06	0.82	1.82*
32	74	0.09	0.96	0.88	1.96*
33	74	-0.10	-1.07	0.79	1.83*
34	74	0.20	1.20	0.98	2.12**
35	72	0.53	1.79*	1.72	3.39***
36	71	-0.03	-0.31	1.77	3.26***

Appendix 2B: Robustness check on the LT-performance of European companies

Table 8.3: The buy-and-hold abnormal returns are calculated with the MSCI Europe index as benchmark.

		Annual buy-and-hold returns		
	Year	n	Average AR (%)	t-statistic
Europe	1	40	9.60	0.99
	3	30	8.07	0.52

Table 8.4: The average abnormal returns (AR_t) and the cumulative average returns (CAR_t) with the MSCI EU index as benchmark.

Seasoning month	Number of firms	AR_t %	t-statistic	$CAR_{1,t}$ %	t-statistic
1	41	0.18e^-2	0.02		
2	41	0.25	2.70**	0.26	1.69*
3	41	0.10	1.27	0.36	2.01*
4	41	0.63e^-2	0.07	0.36	1.84*
5	40	0.06	0.89	0.42	1.84*
6	40	-0.07	-0.78	0.35	1.29
7	40	0.07	1.06	0.43	1.52
8	40	-0.03	-0.26	0.40	1.35
9	40	-0.08	-0.60	0.32	1.00
10	40	-0.06	-0.46	0.26	0.72
11	40	0.78e^-2	0.06	0.27	0.67
12	40	0.06	0.55	0.33	0.80
13	40	-0.26e^-2	-0.02	0.33	0.70

14	39	-0.05	-0.25	0.29	0.67
15	39	-0.04	-0.38	0.26	0.57
16	39	-0.08	-0.73	0.18	0.39
17	38	-0.11	-0.70	0.06	0.12
18	37	0.06	0.40	0.23	0.40
19	37	0.06	0.61	0.29	0.51
20	37	0.04	0.27	0.32	0.56
21	36	-0.07	-0.31	0.34	0.55
22	36	-0.07	-0.38	0.27	0.40
23	36	0.12	1.20	0.39	0.56
24	36	0.07	0.77	0.46	0.63
25	34	-0.07	-0.56	0.26	0.34
26	34	0.83e^-2	0.07	0.27	0.35
27	34	0.18	1.83	0.45	0.57
28	34	0.14e^-2	0.01	0.45	0.58
29	34	0.01	0.08	0.46	0.59
30	32	5.46e^-4	0.23e^-2	0.13	0.17
31	31	0.05	0.41	0.18	0.24
32	31	-0.02	-0.14	0.17	0.21
33	31	0.04	0.28	0.21	0.27
34	30	0.10	0.68	0.25	0.31
35	30	0.11	0.97	0.36	0.42
36	30	0.08	0.72	0.43	0.49