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Master's Thesis

IPO Performance of Fintech Companies from Europe and the United States

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This research analyzes the short-and long-run post-IPO performance of fintech companies from Europe and the United States compared to the financial industry as a whole. For the short-term, issues from the fintech industry tend to be more underpriced as the initial first-day returns are significantly higher, even when controlled for several firm, offer and market characteristics. This effect is substantiated by the fact that firms form the fintech industry are prone to higher levels of ex-ante uncertainty and is, despite a small difference, found to be stronger in the United States than in Europe. There is not any evidence found for higher levels of underperformance for fintech companies in the first and three year(s) after the issue. In fact, they tend to perform better than firms from the financial industry as a whole. The results of this research can be useful for fintech firms that are to conduct an IPO, as they could increase their offer price and leave less money on the table. For the investors, these findings show that the short-term gains of the first-day returns tend not to be offset by long-term losses and fintech firms could therefore be considered as profitable investments.

Keywords: Fintech, underpricing, underperformance, IPO performance, Europe, United States

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1. Introduction

In 2018, Dutch payment platform company Adyen went public by bringing 13,4% of their shares to the market. The initial public offering was a success and the company saw its value double to more than 13 billion dollars on the first day of trading. The share price was estimated at \$240, but reached a price of \$480 after just an hour of trading on the market and eventually closed at \$462.95, resulting in an initial return of 93% (Ram, 2018). The current market value of Adyen is estimated at around 60 billion dollars, making it one of the biggest fintech companies in the world.[1]

Fintech companies arise when Finance and Technology are combined. ‘As an umbrella term, fintech encompasses innovative financial solutions enabled by technology and, in addition, is often used for start-up companies who deliver those solutions, although it also includes the incumbent financial services providers like banks and insurers’ (Puschmann, 2017). KPMG (2021) divides the industry into six different segments: Payments, Insurtech, Regtech, Wealthtech, Blockchain/Cryptocurrency and Cybersecurity. It is thus a broad concept that covers a wide range of services, some of which are already indispensable in people’s everyday life. Following the global outbreak of the COVID-19 pandemic, the size of the global online shopping industry rose to nearly 4 trillion dollars in 2020 and is expecting to exceed this number in 2021.[2] The payments when buying products and services online are processed by platforms such as aforementioned Adyen and it’s American equivalent Paypal. The fintech industry also includes companies that operate in the cryptocurrency industry, a market that has evolved at unprecedented speed over the course of its short lifespan, with the rise of Bitcoin being it’s prime example (Farell, 2015). In 2017, Schueffel stated that ‘the fintech genie is out of the bottle’. At the time, the industry was still at its early years with reported global investments of around \$23 billion (Skan et al., 2016). The accuracy of Schueffel’s claim is emphasized by the most recent figures: \$168 billion and \$105 billion in 2019 and 2020 respectively (KPMG, 2021). Because of its innovative character, fintech has the potential to disrupt the financial services industry

[1] Source: Google Finance
[2] Source: Statista

(Ferreira et al., 2015). It is clearly not to be ignored and could have a lasting impact on the entire finance sector (Heap and Pollari, 2015). However, despite the industry growing in size and gaining more recognition, there has been little academic research that explored the area (Shim & Shin, 2016). The aim of this thesis is to contribute to the academic research about the industry by studying the initial public offering (IPO) performance of fintech companies in Europe and the United States.

An initial public offering is the process of a private company going public by selling newly issued shares on the public stock market for the first time. The main reason for companies to do so is to raise new capital for investments, or to provide their current shareholders with the opportunity to convert some of their wealth into cash in the future (J. R. Ritter & Welch, 2002).[3] Ritter & Welch (2002) mention increased publicity for the company as another consideration for going public. However, they state that most entrepreneurs would rather focus on running their firms than concern themselves with the complex process of going public, just for some publicity in financial newspapers and websites. The complexity of the process already starts by selecting the investment bank that will advise the firm and provide the underwriting services. Issuers look to the abilities of the underwriters who offer their services, but underwriters also look to the quality of the issuers who wish to employ their services (Fernando et al., 2005). The quality and reputation of the underwriter has an effect on the pricing, and therefore, the capital raised by the IPO (Chemmanur & Krishnan, 2012). The complexity of the process is not the only concern that firms should take into account when considering an IPO; there are numerous costs involved in bringing a company to the market. such as legal, printing and auditing fees (Ang & Brau, 2002). Ritter (1987) also counts the gross underwriter spread and the initial underpricing as costs of going public. The underwriter spread is the sum of the management, underwriting and selling fees.[4] Underpricing is known as the phenomenon at initial public offerings where the price after the first day or month of trading is above its initial offer price, resulting in positive initial returns. Another common phenomenon at initial public offerings is the tendency of the stocks to perform worse than their already lister pears in the long run. This anomaly is known as underperformance.

[3] By creating a public market in which they can sell their shares, the shareholders have the possibility to sell (some of) their shares in the future.

[4] The management fee is paid to the lead managers(s); the underwriting fee is paid to the lead and comanagers of the purchasing group; and the selling fee is paid to the selling group (lead, comanagers and syndicate members) (Ritter, 1987).

Initial public offerings and their performances have been studied extensively by academic literature. However, research on the IPO performance of the fintech industry is practically nonexistent or very primitive. It is not common to focus on the IPO performance of a specific sector or industry. For some, usually new and rising industries, it might be interesting to do so and compare the outcomes to other industries. Beck (2017) studied the levels of underpricing in the tech industry and compared them to firms outside the tech industry. The analysis does not find evidence of higher levels of underpricing for the tech industry. Another research focused on one particular sector is Guo et al. (2005), who study the IPO valuation in the biotech industry. They find an underpricing of 13% for the biotech companies, which is lower than the non-biotech companies they are compared with. In the long-run, their sample of biotech companies underperformed the matched portfolio by 14.32%, but this excess return is not statistically different from zero.

This paper has a similar approach as Beck (2017). While he focuses on the levels of underpricing of the tech industry as a whole, the focus in this research will be on the fintech industry in particular. As stated before, fintech is a fast-growing industry with the potential to disrupt the entire finance sector, which makes it more than relevant to examine its levels of underpricing. The potential of the firms and the corresponding hype might lead to consistently high offer prices and subsequently lower underpricing, while on the other hand the higher grade of uncertainty might result higher levels of underpricing. Additionally, also the long-term underperformance will be examined. Findings of patterns of significant underperformance in the long-run for fintech companies might be of interest for investors and firms that are thinking of going public. The hype and irrational optimism about fintech firms might drive the prices above their intrinsic values, causing the firms to perform worse in the long run. On the other hand, there have been examples of firms such as Adyen, performing very well in the years after their IPO.

The markets of Europe and the US have major differences in terms of regulation, size, underwriters and currencies. These differences will also have their effect on the IPO performance. Ritter (2003) states that the US market historically is a lot bigger than the European market in terms of volume of IPO’s. However, during the dot com bubble, the European market exceeded the Americans in 1998, 1999 and 2000. Ljungqvist & Wilhelm (2003) document that European underwriters receive lower fees than their American peers and suggest that this might have an effect on the offer price. It is therefore relevant to examine the differences between the European and American fintech market in terms of underpricing and underperformance, as any variation in initial returns and long-term performance might also be of interest to the investors and the firms itself. Furthermore, this geographical distinction can be used to see if there are particular fintech segments that either US or European firms stand out in.

In summary, this paper analyzes the short- and long-term post-IPO performance of companies in the fintech sector located in the United States and Europe that went public between 2008 and 2020. It will study if companies within the fintech sector experience significantly higher levels for the two major anomalies for initial public offerings presented in the literature, being underpricing and underperformance, when they are compared to companies of the financial sector as a whole. This results in the following research question:

Do fintech companies from Europe and the United States experience higher levels of underpricing and underperformance when compared to companies from the financial sector as a whole?

In line with the literature, this is tested by performing Ordinary Least Squared (OLS) regression analyses on the initial first-day returns and cumulative abnormal returns of financial firms that conducted an IPO between 2008 and 2020, with a dummy variable that takes the value of 1 if the company is classified as fintech and control variables that control for several firm, offer and market characteristics used as independent variables. The comparison between Europe and the United States is conducted by measuring interaction effects. Furthermore, the total sample is divided by region to see the differences in the complete analyses.

Evidence is found on fintech companies to experience significantly higher levels of underpricing, even after adding all the control variables to the analysis and variables that control for the year in which the IPO took place and for the firms being located in either Europe of the United States. When analyzing the differences in the magnitude of the effect between the two regions, the results show that the effect is significantly present in both of the regions and stronger by a small amount in the United States. There is not any evidence found confirming the presence of long-run underperformance for fintech firms. When using the MSCI World index as the benchmark return, fintech firms even show significantly higher abnormal returns in the three years after going public than their non-fintech peers included in the sample. This tendency of fintech firms to outperform the rest of the firms of the sample in the period after the IPOs tends to be stronger in Europe. However, as no significant relationship is found when the companies are divided by region, no confident claims on the differences between these regions can be made.

The main contribution of this research is that it provides an insight on the short- and long-run post-IPO stock performances of companies from the fintech industry by testing if the two biggest anomalies for initial public offerings hold for that particular industry. Furthermore, it analyzes the differences between Europe and the United States in the stock performance of fintech companies after their issue. Despite being used to control for firm, offer and market characteristics, the results of the control variables also provide an insight on the effect that these variables have on the initial returns and cumulative abnormal returns. For instance, when the sample is divided by region, some interesting differences in the firms that are venture capital backed are presented. This introduction is followed by an in-depth overview of the most relevant existing literature on both underpricing and underperformance, arising in the hypotheses that will be tested. After that, there will be a chapter dedicated to point out the process of the data collection and operationalization. Next up is the methodology, where the methods and the variables used to test the hypotheses are explained extensively. The results are outlined in the chapter after that, resulting in a conclusion. At last, the limitations of the study are outlined and discussed as well as recommendations for further research.

2. Literature review & hypotheses

2.1 Short-run underpricing

Underpricing is known as the phenomenon at initial public offerings where the price after the first day or month of trading is above its initial offer price, resulting in positive initial returns. One of the first to find significant positive initial returns was Ibbotson (1975) when studying the initial and aftermarket performance of newly issued stocks in the US during the 1960's. He reports an average initial return of 11.4%, which is measured as the difference between the offer price and the stock price after one month. The author states that these numbers suggest that either the offering price is set too low or the investors overvalue new issues at the end of the first month. Ritter (1984) extended this time frame and studied the initial returns for 5000 newly issued companies from the United States and found an average underpricing of 18.8% between 1960 and 1982. In contrast to Ibbotson (1975), Ritter uses the first day return as the measure for initial returns. In his most recent publication of US IPO statistics for 2020 and earlier years, a mean first-day return of 16.7% for the most recent period of 2001-2020 and 18.4% for the total period of 1980-2017 are reported.[5]

There is also plenty of evidence for the existence of an underpricing pattern in the European market. When studying French equity offerings between 1992 and 1998, Derrien & Womack (2003) observe a level of initial underpricing of 13.23%. These findings are strengthened by Ljungqvist & Wilhelm (2002), who report initial returns of 16.5% for French IPO's over the period 1990-2000. The latter authors find underpricing levels of 40.2% and 39.6% for Germany and the United Kingdom respectively, while Cassia et al. (2004) analyze IPOs listed on the Italian Stock Exchange from 1985 to 2001 and find significant first-day returns of 21.87%.

Ritter (2003) provides an overview of average initial return percentages for most of the European countries when studying the differences between the European and American IPO markets and recently published an updated version of these statistics.[6] He finds positive average initial returns for all the European countries when looking at the past 30 tot 50 years.[7]

[5] Remark for 1980-2017: during the dot com bubble of 1999-2000, an average initial return of 64,6% is reported (Ritter, 2017)

[6] The statistics were last updated on March 22, 2021 (Ritter et al., 2021)

[7] The countries and their corresponding percentages/time frames are: Belgium (11.0%; 1984-2017), Denmark (7.4%; 1984-2017), Finland (14.2%; 1971-2018), Germany (21.8%; 1978-2020), Greece (50.8%; 1976-2013), Ireland (21.6%; 1991-2013), Italy (13.1%; 1985-2018),

Despite some variation in the percentages, the initial returns are thus consistently positive. This indicates that when companies go public, the equity sold in the initial public offering tends to be underpriced (Ljungqvist, 2007). This is a cost to the issuer, as they could have asked a higher price for the equity offered on the market. These costs are described as 'the money left on the table' by Loughran & Ritter (2002) and are calculated as the first-day price gain multiplied by the number of shares sold. The explanation proposed by the authors as to why the issuers do not get upset about these profits that they miss out on is related to the prospect theory.[8] They care less about what they could have earned than the actual cost paid to the underwriter. Additionally, at the same time that the underpricing is diluting the pre-issue shareholders of the firm,[9] they receive the news that their wealth is much bigger than anticipated.

It is already mentioned that the issuing company has to pay the underwriter for its services, which is usually an investment banker. Baron (1982) claims that the underpricing anomaly arises as a consequence of the information asymmetry between an issuer of new securities and an investment banker. The underwriter is better informed about the capital market's demand and in order to be compensated for sharing that information with the issuer, underpricing occurs. This would automatically mean that for issuers that are more uncertain about the market reaction to its issue, the level of underpricing will be higher.[10] Ritter (1987) strengthens that theory by presenting evidence of two cost components when going public; The direct costs, primarily being the fees paid to investment bankers, and the indirect cost of underpricing. Muscarella & Vetsuypens (1989) contradict Baron's line of reasoning by examining self-marketed IPO's.[11] Giving the fact that the issuer and the underwriter are the same, there cannot be any information asymmetry and underpricing should be non-existent for these IPO's. However, they find that these self-marketed IPO's experience significant first-day returns of around 7%. Those numbers of initial returns are not statistically different from 'normal' IPOs of equivalent size.

Netherlands (13.3%, 1983-2017), Norway (6.7%, 1984-2018), Poland (11.7%, 1991-2019), Portugal (11.5%, 1992-2017), Russia (3.3%, 1999-2013), Spain (9.2%, 1986-2018), Sweden (25.9%, 1980-2015), Switzerland (25.2%, 1983-2018) and Turkey (9.6%, 1990-2014) (Ritter, 2021).

[8] People tend to think in terms of gains and losses rather than in terms of their net wealth (Kahneman & Tversky, 1979)

[9] The same amount of money could have been raised with less amount of shares at a higher price, causing the shareholder to hold a larger stake in the company

[10] As they are willing to pay more for the information about the market

[11] Self-marketed IPOs are Initial public offerings of investment bankers who market their own securities

Another explanation that also has to do with asymmetric information is the one provided by Rock (1986). He applies the adverse selection concept known as the winner's curse to the IPO market.[12] His model considers an initial public offering as an auction with informed and uninformed investors acting as the bidders. The overvalued issues tend to be won by uninformed investors, as the informed investors crowd them out of underpriced new issues. This would mean that if new issues were not consistently underpriced, uninformed investors would achieve negative returns and eventually withdraw from bidding. To prevent this from happening, the equilibrium offer price set by investment bankers deliberately includes a finite discount in order to attract uninformed investors. Beatty & Ritter (1986) use Rock's model to underpin their argument that underpricing will be higher for issues of which the ex-ante uncertainty about their market value is higher. Additionally, they argue that the investment banker has to enforce the underpricing equilibrium because it will otherwise be penalized by the marketplace; either by losing investors when not underpricing enough, or losing issuers when underpricing too much.

As stated before, the underwriter is more informed about the capital market and its demand than the firm going public. However, the best information about the firm's prospect is held by the firm itself (Allen & Faulhaber, 1989). By underpricing their newly issued equity on the market, firms enable the institutional investors to make a profit by selling their shares, which they bought for the offer price, for a higher price on the secondary market. Furthermore, as deliberately underpricing the equity is a cost to the issuer, investors know that only high-quality firms will be able to afford doing so. Companies can recoup the money left on the table by seasoned equity offerings (SEO): returning to the market on a future date to issue additional shares. These shares can be sold at attractive prices, as the institutional investors are still left with the "good taste in their mouths" by the previous issue and the associated profits (Ibbotson, 1975). Additionally, IPOs with high initial returns usually attract a lot of media attention. This publicity about the previous issue will make the additional issued shares highly-anticipated by investors, enabling the firm to set a high offer price. This rationale for explaining underpricing is known as the signaling theory (Allen & Faulhaber, 1989). Support for this theory is found by Jegadeesh et al. (1993) when they observed a positive relationship between IPO underpricing and SEO proceeds.

[12] Winner's curse: In an auction, the winning bid tends to exceed the (intrinsic) value of the item that is auctioned (Thaler, 1988).

In the literature, powerful rationales and corresponding evidence for a positive relationship between ex-ante uncertainty and the level of underpricing is provided. For firms of which the uncertainty about the future market value is higher, the initial returns after their issue will be higher (Beatty and Ritter, 1986; Rock, 1986). This claim is supported by Grinblatt & Hwang (1989), who find a positive relationship between the riskiness of a project and the level of underpricing.

For fintech firms, there typically is a higher grade of uncertainty. First of all, the cash flows of tech firms tend to be more volatile and the assets they carry are mainly intangible,[13] making them more vulnerable to financial distress (Kim et al., 2008). Second, the tech sector is of course an innovative one, making it inherently unpredictable. Karlis (2008), who found evidence that internet companies tend to be more underpriced as opposed to companies that do not use the internet as a main line of business, allocate these findings mainly to fact that internet companies that are going public are relatively young in terms of age. For the fintech sector, the uncertainty is more critical than other tech sectors, as the transactions and activities of its firms are more complicated and therefore less predictable (Ryu & Ko, 2020). As it is also quite a new sector, there is still much uncertainty about the stability of these firms in the long term. As mentioned before, the hype around fintech reminds some of the internet bubble of 1999 and 2000 (Cumming & Schwienbacher, 2018). During that period, there was an excessive speculation in internet-related companies with a period of massive growth and extremely high first-day returns as a result (Ljungqvist & Wilhelm, 2003). When the bubble burst, there was an enormous free fall on the Dow and NASDAQ and suddenly internet companies had to prove if they would even be able to make a profit at all (Goodnight & Green, 2010). Despite the potential of fintech companies, the fear of a repeat of such a freefall could cause investors to be reluctant about the stability of these firms in the long run, increasing the uncertainty.

Taking all of this into account, it is expected that the level of underpricing will be higher and more significant for fintech firms when compared to firms of the entire financial sector:

H1: In the short run, underpricing is significantly higher for Fintech companies when compared to companies of the financial industry as a whole.

[13] Patents and other intellectual property

As previously mentioned, the stock market of Europe and the United States have different characteristics which of course has an effect on the IPO markets and, subsequently, on first- day returns. The IPO market of Europe has historically been dwarfed by its American equivalent. The volume of firms going public has always been much higher in the US than in Europe. This mainly has to do with the fact that European stock exchanges had listing requirements for firms that want to go public, such as having three years of positive earnings (Ritter, 2003). Recently, these requirements have been focused on disclosure and governance instead of financial requirements, causing a rise in the volume of IPOs (Giudici & Roosenboom, 2002). During the internet bubble, the European IPO volume even exceeded that of the USA when including the United Kingdom. However, despite these exceptions, the IPO market of the United States is thus less regulated and bigger than that of Europe. Furthermore, European firms going public tend to be much older than those that go public in the United States. This could of course be an effect of the financial requirements that European markets set on firms that want to go public (J. R. Ritter, 2003). Another important difference between European and US practice is the difference in legal risk. For instance, class action lawsuits are common in the USA, but rare in Europe.[14] This mitigates the legal risk in the United States, while legal risk is one of the main reasons that high quality underwriters are less likely to take riskier companies public in Europe (van der Goot, 2003). These differences cause the underpricing to be relatively higher in the US, due to a higher grade of uncertainty. On the other hand, the fees charged by underwriters of European IPOs are lower than those in the USA (Ljungqvist & Wilhelm, 2003). The authors report that the American underwriters are therefore more willing to revise the offer price upwards and find a tradeoff between the gross spreads, being the fees charged by the underwriter, and the level of underpricing. This might result in higher underpricing levels in Europe. However, taking the beforementioned differences into account, more fintech companies with higher grades of uncertainty will be able to go public in the US. This will result in higher levels of underpricing for those companies. Therefore, the effect of a higher level of underpricing for fintech companies is expected to be higher in the United States than in Europe:

H1a: The effect of higher underpricing levels of fintech companies compared to the financial industry as a whole is higher in the United States than in Europe.

[14] Class action lawsuits overcomes the free-rider problem that the plaintiff (Suing party) pays al the costs but only enjoys part of the benefits if all the shareholders are harmed.

2.2 Long-run underperformance

The efficient market hypothesis (Malkiel & Fama, 1970) suggest that the stock price should reflect its true intrinsic value once the IPO is publicly traded and that no predictable patterns should be visible. However, they appear to perform worse when compared to its already listed peers in the long run. This anomaly is known as underperformance.

One of the first studies to address this anomaly was Ritter in 1991 stating that in the long-run, initial public offerings tend to be overpriced. He builds on the research of Ibbotson (1975), who concluded that the "results generally confirm that there are no departures from market efficiency in the aftermarket" (p. 265). However, despite showing relatively high standard errors, Ibbotson finds negative performances relative to the market for the three years after the IPO. Ritter (1991) studies a sample of 1,526 common stock IPOs over the period 1975-1984 in the US and finds an average return of 34,47% for the three years after going public, while a sample matched by industry and market size containing non-issuing firms shows an average return of 61,68% over the same period. When the abnormal returns relative to different benchmarks are calculated, the underperformance of the IPOs is both economically and statistically significant. Additionally, Ritter (1991) finds a pattern indicating that the underperformance is mostly concentrated among relatively young growth firms. This is in line with the tendency of firms to go public when investors are irrationally optimistic about the future potential of certain industries. Ritter follows Shiller (1990) by referring to this theory as the fads explanation.[15]

This pattern of IPO stocks to underperform is emphasized when studying the returns of firms issuing stocks during 1970 to 1990. If you would want to end up with the same amount of wealth five years after the date of going public, the investment has to be 44% larger when investing in issuing firms as opposed to similar non-issuing firm (Loughran & Ritter, 1995). The authors state that the underperformance is due to firms taking advantage of the window of opportunity that arises when firms of specific sectors are considerably overvalued. This is in line with the findings of Ritter (1991) that firms tend to go public near the peak of industry-specific fads.

[15] Fads is the conjecture that market prices of securities thrift away from their fundamental value which it eventually will return to (Bollarslev & Hodrick (1992)

More evidence of poor post-IPO long run performance is found by Ritter & Welch (2002), when analyzing the behavior of newly issued stocks in the United States three years after going public for the period 1980-2001. When the abnormal buy-and-hold returns are calculated, the IPO's show an underperformance of 23.4% relative to the market portfolio and 5.1% relative to similar companies based on market capitalization and book-to-market ratio. However, they make the comment that these results are sensitive to both the method used and the time frame that is being considered.

This pattern of IPOs to perform worse in the long-run is also present for the European market. Berk & Peterle (2015) took a sample of 172 companies going public in the emerging markets of Central and Eastern Europe for the period 2000-2009 and find evidence of significant underperformance. When comparing these results to the developed EU markets, they find that the post-IPO performance of companies in the developed markets is even worse.[16] They also indicate the tendency of smaller companies to perform worse in the three years after going public than the companies that have a bigger deal size, which is in line with the findings of Ritter (1991). Additionally, the authors find evidence of much greater underperformance for companies that delist in the years after going public than for the companies that survive. In contrary to Berk & Peterle (2015), who investigated very different European markets, Gandolfi et al. (2018) consider a homogeneous Eurozone context consisting of three markets: Italy, France and Germany.[17] When studying the long run performance of companies going public in these countries over the period 1997-2011, a negative overall trend is revealed. The cumulative abnormal returns and buy-and-hold returns both show significant negative values after 6 months for the entire Eurozone, which are confirmed at 1 and 3 years. However, the underperformance is quite low when compared to other countries, such as the United States. Furthermore, the trend differs between the studied countries: the IPO shares in Germany tend to maintain their returns, in France they gradually worsened and in Italy the performance improved over time. The authors also mention that despite the findings that the industries are not a determinant for the performance of the stocks, the technological sector shows slightly higher trends in long-run post-IPO performance.

[16] For the emerging markets the stock exchanges of Austria, Bulgaria, the Czech Republic, Poland, Romania and Slovenia are included in the sample. For the comparison with the developed capital markets the Borsa Italiana, Deutsche Boerse, London SE and NYSE Euronext are used.

[17] These countries have a common currency and a centralized banking system (ECB). Additionally, they are the most populated countries in Europe and their combined GDP represents almost 50% of the European Union (Gandolfi et al., 2018).

Purnanandam & Swaminathan (2004) follow the rationale that if security prices tend not to be efficient in the short run, the closing price after the first trading day cannot be used as a reference of the fair value of the firm. The long run performance of the public offering should therefore be compared to another fair value determinant by computing a price-to-value ratio. The value would then be the intrinsic value of the company, which is determined by the performance of the company over a longer period of time.[18]

Carter et al. (1998) study the effect that the reputation of the underwriter has on the long-term performance. They find that the underperformance becomes less severe as the underwriter reputation increases. Loughran & Ritter (1995) stated that investing in the firms going public might be hazardous to one's wealth. Despite finding significant evidence that supports this claim, Carter et al. (1998) establish that investing in IPO's underwritten by high-reputation underwriters thus mitigates this risk. Brav & Gompers (1997) state that underperformance is not an IPO effect, but rather a characteristic of small, low book-to-market firms. By replicating the results of Ritter (1991) and Loughran and Ritter (1995), they find that the underperformance documented is mainly due to smaller, non-venture capital backed firms. The returns of nonventure-backed firms are significantly lower than those of venture-backed firms and relevant benchmarks. They conclude that venture backed firms outperform non-venture backed firms and do not significantly underperform.

The literature agrees on the fact that the tendency of firms to go public when investors are irrationally optimistic about the future potential of certain industries is one of the biggest causes of firms to underperform in the long run. Fintech certainly is an industry prone to investors' sentiment driving the prices above their intrinsic value. Cumming & Schwienbacher (2018) state that there has been an increasing amount of hype about fintech in recent years and that this hype is sufficient to remind some practitioners of the dot com bubble. Additionally, Ofek & Richardson (2003) and Ljungqvist & Wilhelm (2003) provide evidence of significantly higher underperformance amongst new technology firms. The following is therefore expected:

H2: In the long-run, underperformance is significantly higher for Fintech when compared to companies of the entire financial industry as a whole.

[18] The fair/intrinsic value of the company is computed by using multiples based on the firms' sales, earnings, or EBIT(DA).

The beforementioned differences between the European and American IPO market also has its effect on the long-term stock performance of firms going public. There are more firms with a higher grade of long-term uncertainty going public in the United States than in Europe because of the difference in size, regulations and legal state. Companies that go public also tend to be younger in the United States. When investors are optimistic about the potential of a certain industry, it would be easier to conduct an IPO for a young growth firm in such an industry in the US than it would be in Europe, where there are more requirements on firms that want to go public. The fintech industry is, of course, prone to these kinds of young growth IPOs. Ritter (1991), amongst others, finds that these relatively young growth firms are usually the firms that show underperformance relative to the market. One could therefore expect these levels of underperformance in the fintech sector to be higher in the United States. This claim is supported by the results of Gandolfi et al. (2018), who report that the levels of underperformance in Europe are quite low in comparison to the United States. The following is therefore expected:

H2a: The effect of higher underperformance levels of fintech companies compared to the financial industry as a whole is higher in the United States than in Europe.

3. Data

The data is collected from Thomson One, Eikon Datastream and Zephyr. Thomson One is used for selecting the initial sample and retrieving data on the offer dates and prices, number of shares offered, underwriter names, nation/continent of headquarters, founding year and the firms being venture capital backed or not. Eikon Datastream is the main database used to retrieve the data of the indices that are included in the analysis and the company financials, such as revenues and the closing price of the stock one day after the offer. Furthermore, Zephyr is consulted to supplement missing values in the data retrieved via Eikon Datastream and Thomson One. The process of selecting the sample is described in detail hereafter. There will also be an overview of how many companies are included in the eventual sample and how many of those are classified as fintech. As the samples are divided into two sub-samples to draw comparisons between Europe and the United States later on, the distribution between those regions is also displayed.

3.1 Sample selection

Like stated before, fintech is a broad concept that covers a wide range of services; No one single definition of fintech exists (Schueffel, 2017). As the fintech industry fintech does not have its own SIC code, it is important to determine the definition that is used to select the companies that are considered as 'fintech' for this research. I choose to follow the method applied by Dranev et al. (2019). Firms are considered as fintech whenever they have the SIC code related to both the finance industry and the technology sector. The major SIC groups used for the financial sector are the following:

(i) SIC code 60 – Depository Institutions,
(ii) SIC code 61 – Non-depository Credit Institutions,
(iii) SIC code 62 – Security and Commodity Brokers, Dealers, Exchanges and Services,
(iv) SIC code 63- Insurance Carriers
(v) SIC code 87 – Engineering, Accounting, Research, Management, and Related Services.

The fintech sector will be compared to the financial sector as a whole. Therefore, all the firms with SIC codes 60-67 or 87-89 with IPO's in either Europe or the United States are included in the sample. The firms classified as fintech are the firms that have the SIC codes 7371-7374 as well, as these are the SIC codes that belong to the technological industry. Another important aspect in the process of selecting the sample is establishing the time frame that is being considered. The sample period consists of the years 2008–2020. By considering this period, the housing bubble before the financial crisis of 2008 is being ignored, as it would have a significant effect on the underpricing levels. Including the period of the financial crisis in the analysis will inevitably also have its effect on the underpricing levels, as it caused investors to be more risk averse (Guiso et al., 2018). However, the financial crisis of 2008 is seen as one of the main reasons that the Fintech sector has evolved into a new paradigm (Arner et al., 2015). It will therefore be used as the starting point of the sample period. For the long-run underperformance the examined period will decline to 2008-2017, as we measure stock performances for a period up to three years after the IPOs. Consistent with prior studies about initial public offerings, there are some exclusions from the sample. First of all, 'penny stocks' are excluded from the analysis, as they are considered as highly volatile and only a small rise in absolute value would result in high underpricing values. Chambers & Dimson (2009) exclude all stocks with an offer price of 10 pence or less, while Liu & Ritter (2011) take an offer price of $5.00 per share as the lower boundary. For this research, alle stocks with an offer price below $1.00 per share are excluded from the sample. Additionally, the acquisition corporations are excluded from the sample due to limited data availability. This means that all the companies with solely the SIC Code 6726 are excluded.[19] For the short-term sample, values that have missing data on the stock price one day after the offer are excluded from the sample, as it is not possible to calculate the first-day initial return for those companies. For the long-term sample, values that have missing data on the long-term stock prices are excluded, as it is not possible to calculate the cumulative abnormal returns. The handling of missing data in any of the independent variables is described in chapter 4.3: Independent Variables. In the table below, an overview of the sample composition and the number of firms included in the samples is provided, as well as how many of those firms are classified as fintech and the distribution per region.

TABLE 1. DETAILED OVERVIEW OF THE SAMPLE COMPOSITION

Number of IPOs of financial firms issued in the period 2008-2020	2194	
Companies with an offer price below $1.00	(166)	
Acquisition corporations	(649)	
Missing values on stock price 1 day after offer	(92)	
Final short-term sample	**1287**	
Fintech		115
United States		599
Europe		688
Companies with IPO dates in 2018-2020	(332)	
Missing values on long-term stock prices	(56)	
Final long-term sample	**899**	
Fintech		87
United States		373
Europe		526

An overview of the sample composition process including the corresponding number of values per step. Furthermore, the number of companies included in the final samples are displayed, as well as how many of those are classified as fintech and the distribution per region (Europe or the United States). The sample is retrieved from Thomson One.

19 Companies with SIC Code 6726 as well as another SIC code remain included in the sample.

4. Methodology

This research consists of both a short- and long-run study on post-IPO stock performance. Therefore, various number of performance measures and variables are used in order to conduct the analysis. In this chapter, the research design to test the hypotheses is elaborated, as well as an overview of the dependent and independent variables and how they are computed. After that, the descriptive statistics of the control variables are displayed and shortly elucidated, including a correlation matrix to analyze the relation that these variables have with fintech companies. An overview of the dependent variables, being the initial returns and the cumulative abnormal returns, are turned to in the Results chapter.

4.1. Research design

This study uses quantitative statistical analysis to test the hypotheses and answer the main question. By testing the hypotheses, conclusions on whether or not fintech companies show different short-and long-run post-IPO performance as opposed to the financial sector as a whole can be drawn, as well as differences in the magnitude and significance of the effect between Europe and the United States.

To test hypothesis *H1*, I follow the method of Carter et al. (1998) and make use of a regression with the underpricing, measured as the first-day initial returns, as the dependent variable. As the first-day initial returns are measured in a specific point of time, a cross-sectional analysis is suitable. In line with previous research, an Ordinary Least Squared (OLS) regression will be performed (Loughran & Ritter, 2004).[20] If the coefficient of the *DFINTECH* variable is significantly positive, it can be concluded that the underpricing is higher for fintech firms. To assess the marginal impact of the firm being fintech on the underpricing, a number of independent variables are included to control for firm-, offer- and market characteristics. These variables are elaborated in section 4.3. For every control variable added, a new regression is being run to check its impact on the analysis and the other coefficients. After adding all the

[20] The Ordinary Least Squared (OLS) model assumes a linear relationship between the dependent and independent variables. The coefficients are estimated such that the sum of the squared residuals is minimized.

control variables, a region dummy variable that controls for the differences in region and a variable that controls for the year in which the IPO took place will be added to the analysis as this increases the significance of the results. The complete regression looks like the following:

$$IR = a_i + \beta_1 DFINTECH + \beta_2 AGE + \beta_3 REVENUE + \beta_4 DVENTCAP + \beta_5 PROCEEDS + \beta_6 DHQ\_UNDRW + \beta_7 INDEX\_WORLD + \beta_8 REGION + \beta_9 YEAR + e_i$$

To test hypothesis *H1a*, first an interaction term between the region dummy and the fintech dummy is included in the analysis to analyze whether the effect differs between these regions. Giving the way the region dummy and the interaction term are constructed,[21] a positive interaction term would indicate that the underpricing for fintech companies is higher in Europe. Logically, a negative coefficient would then mean that the underpricing of fintech companies is higher in the United States. Furthermore, the sample is divided in two: European firms and firms from the United States. This is done in order to be able to analyze the differences between the complete regression models of both regions. The effect of adding the control variables to the entire model and the fintech variable is visible for both regions, as well as the differences in the coefficients and explanatory power of the model. As the sample is already split into the two regions, it is meaningless to include the region dummy in those analyses. However, the variable that controls for the year of the IPO is still included in the analysis. This results in the following regression equation for the two sub-samples:

$$IR = a_i + \beta_1 DFINTECH + \beta_2 AGE + \beta_3 REVENUE + \beta_4 DVENTCAP + \beta_5 PROCEEDS + \beta_6 DHQ\_UNDRW + \beta_7 INDEX\_REGION + \beta_8 INTERESTRATE + \beta_9 YEAR + e_i$$

[21] The region dummy is constructed in such manner that Europe is classified as '1' and United States is classified as '2'. As the United States companies are omitted and used as a benchmark in the interaction term, the coefficient of the interaction term indicates the effect that 'changing' from United States to Europe has on the underpricing of fintech firms.

Conducting cross-sectional OLS regression models is also the most appropriate method to test hypothesis *H2*. In these regressions, the 1- and 3-year cumulative abnormal returns are used as the dependent variables. The independent variables used to test the hypotheses and to control for firm-, offer- and market characteristics are the same as in the short-run analysis. Additionally, the variable *DDELIST_36* is added to the regression to control for the early delisting of companies.[22] The complete model then looks like the following:

$$CAAR_{i,t} = a_i + \beta_1 DFINTECH + \beta_2 AGE + \beta_3 REVENUE + \beta_4 DVENTCAP + \beta_5 PROCEEDS + \beta_6 DHQ\_UNDRW + \beta_7 INDEX\_WORLD + \beta_8 DDELIST\_36 + \beta_9 YEAR + \beta_{10} REGION + e_i$$

To test hypothesis *H2a*, an interaction term between the region dummy and the fintech variable is again included in the analysis to measure the difference in the effect between the regions. A positive coefficient of the interaction term would indicate that the cumulative abnormal returns are higher in Europe than in the United States, which would mean that, if found, the underperformance levels of fintech companies are higher in the United States.[23] For the long-term stock performance, dividing the sample by region is essential, as the indices used as benchmark to calculate the cumulative abnormal returns differ between Europe and the United States. Therefore, these separate analyses are not only used in order to test hypothesis *H2a*, but also help to draw conclusions on hypothesis *H2*. Moreover, conclusions on the differences in the effects between Europe and the United States can be drawn based on the differences in coefficient and significance of the fintech variable. Furthermore, the differences in the effect of adding the control variables to the entire model and the fintech variable is analyzed, as well as the differences in the other coefficients and explanatory power of the model.

$$CAAR_{i,t} = a_i + \beta_1 DFINTECH + \beta_2 AGE + \beta_3 REVENUE + \beta_4 DVENTURECAP + \beta_5 PROCEEDS + \beta_6 DHQ\_UNDRW + \beta_7 INDEX\_REGION + \beta_8 INTERESTRATE + \beta_9 DDELIST\_36 + \beta_{10} YEAR + e_i$$

[22] The elaboration on this variable can be found in chapter 4.3: Independent Variables.

[23] Recall that the region dummy is constructed in such manner that Europe is classified as '1' and United States is classified as '2'. As the United States companies are omitted and used as a benchmark in the interaction term, the coefficient of the interaction term indicates the effect that 'changing' from United States to Europe has on the cumulative abnormal returns of fintech firms.

Before every regression analysis, the residuals are analyzed to indicate if there are any outliers that could potentially have an excessive influence on the analysis. As not all the outliers necessarily have an influence on the analysis, the Cook's distance (COOKSD) and DFITS are used to identify these influential cases. Generally, all the cases that have values of COOKSD and DFITS that are above the threshold set by the rule of thumb are excluded from the analysis.[24] The analysis is then conducted in order to see if the model improved. If so, the rule of thumb is sufficient and therefore followed to exclude these values from the analysis. If this is not the case, the values of COOKSD and DFITS are visually inspected to see which thresholds to apply. It is then verified whether or not the model improved. Logically, this is mainly a trial-and-error process. Which thresholds is applied and the effect this has on the total sample is mentioned for each analysis itself in chapter 5: Results.

One of the assumptions of the OLS-regression model is that the error terms have constant variance. When this is not the case, heteroskedasticity exists. As this could be a major problem when conducting cross-section analyses, it is relevant to include a Breusch-Pagan test for heteroskedasticity in the analysis (Williams, 2010). To check more thoroughly besides the Breusch-Pagan test, the squared residuals are analyzed and a White-General test is run for all the analyses. When these tests indicate signs of heteroskedasticity, clustering the error terms in a robust regression might improve the model. These tests are therefore run for all the regressions that are conducted. If they indicate heteroskedasticity and the significance of the coefficients improves and/or the estimators are of lower variance after including robust standard errors in the model, this is applied for that specific analysis.

4.2. Dependent variables

In this section the calculation of the dependent variables will be elaborated, starting with the short-run underpricing. This will be followed by an overview of which method is used to calculate the long-term underperformance and which indices are used as the benchmark returns.

[24] The rule of thumb sets the threshold for Cook's distance at 4/(N-k-1), where N is the number of observations and k is the number of independent variables included in the analysis. For DFITS, the threshold is set at 2 x √(k/N).

4.2.1. Short-run underpricing

For the short-run performance, almost all of the literature uses the first-day initial returns. Ibbotson (1975) uses the initial returns of the first month after going public, but mentions that using the first-day returns would have had his preference. However, the data only included offer prices and calendar month-end prices. The first trading day initial returns will therefore be used as the indication for underperformance and are calculated by taking the natural logarithm of the first-day closing price divided by the offer price (Ljungqvist, 1997):

$$IR = \ln\left(\frac{Closing\ price}{Offer\ price}\right) \quad (1)$$

A positive figure would thus mean that the offer was underpriced and the issuer left money on the table, whereas a negative figure in first day initial returns would mean that the offer was overpriced.

4.2.2. Long-run underperformance

The analysis of long-run abnormal returns is described as "treacherous" by Lyon et al. (1999), while Kothari & Warner (1997) point out that long-horizon studies should always be treated with "extreme caution". These claims are still supported today as measuring performances over a longer period of time will always have its limitations,[25] resulting in the fact that there has not been a mutual agreement on which model yields the most robust and accurate results. However, the aim of this study is not to reach conclusions as to which method is the superior one.

In the literature, different methods are used to calculate the long-run stock performance. The two main methods that are commonly applied are the cumulative abnormal returns (CAR) and the buy-and-hold abnormal returns (BHAR). Both of these methods are event-time approach methods introduced by Fama et al. (1969), used to test market efficiency.[26] Ritter (1991), amongst others,

[25] The main problem is that all the models for measuring expected return are incomplete descriptions of the systematic patterns in average returns during any sample period. This would result in the fact that tests of efficiency will always be contaminated by a bad-model problem (Fama, 1998). This problem is described by Kothari & Warner (2007) as the joint-test problem: the rejection of any hypothesis regarding long-term abnormal returns might be due to the existence of misspecification rather than mispricing.

[26] In an efficient market, markets adjust rapidly to new information (Fama et al., 1969)

uses the cumulative abnormal returns. This is calculated by the stock's raw monthly return minus a benchmark used for 'normal' market return. However, this method implies monthly portfolio rebalancing and does not take monthly compounding into account, which causes biases (Barber & Lyon, 1997).[27] Others therefore use the buy-and-hold-abnormal returns, which yields more realistic results for investors by including monthly compounding. Fama (1998) argues that despite the BHAR yielding more realistic results, the CAR is the more robust method for long run performances, as buy-and-hold abnormal returns can be magnified due to the single period returns compounding. This implies that when comparing the three- and five-year BHAR of a company that only had abnormal returns in year one, the latter would show higher figures due to compounding. This is in line with Mitchell & Staffor (2000), who argue that using the cumulative abnormal returns is the most appropriate method when defining outperformance. I prefer the more robust method and will therefore use the cumulative abnormal returns (CAR).

To calculate the cumulative abnormal returns, the terminology as used by Ritter (1991) is followed. First of all, the abnormal returns of each stock have to be determined. Ritter (1991) refers to these returns as the benchmark-adjusted returns and calculates them by subtracting the monthly benchmark return from the monthly raw stock return. Ritter (1991), Brav & Gompers (1997) and Brau et al. (2012) all note that the underperformance changes significantly when using different indices; several indices will therefore be used in the analysis. In order to test for hypothesis *H2*, an index that is relevant for both United States and European firms has to be used as firms form both of these regions are included in the sample. Therefore, the MSCI World index is used. To test for hypothesis *H2a*, the benchmark used are the (1) NASDAQ-100 and (2) S&P-500 for the United States sample and the (3) MSCI Europe and (4) STOXX Europe 600 for European companies.[28] In line with Ritter (1991) and Carter et al., (1998), both the value-and equal weighted equivalents of the indices mentioned are used as the results differ significantly.

[27] Barber & Lyon (1997) mention three biases. The first being a measurement bias, which states that cumulative abnormal returns are a biased predictor of long-run buy-and-hold returns. Second, newly listed firms tend to underperform as regard to market averages. Therefore, this new listing bias will lead to positive bias in the population mean of long-run buy-and-hold abnormal returns. Last, the authors mention that the abnormal returns are positively skewed; it is not that hard to find a firm that has an abnormal return of more than 100%, but finding a return of the market index above 100% is highly unlikely. They refer to this as the skewness bias.

[28] Using the NASDAQ Composite index would have been preferred. However, there was no data available for the equal-weighted index.

The benchmark-adjusted return for stock i in event month t is then defined as:

(2) $$ar_{it} = r_{it} - r_{mt}$$

Where a negative benchmark-adjusted return would mean that the stock has been outperformed by the benchmark return, represented by the indices. By using the abnormal returns of all *n* stocks in the sample over months *i* to *t*, the average benchmark adjusted return and is calculated as the equally-weighted arithmetic average of the benchmark-adjusted returns:

(3) $$AR_t = \frac{1}{n}\sum_{i=1}^{n} ar_{it}$$

The cumulative benchmark-adjusted returns from event month t_1 to event month t_2 is the summation of the average benchmark-adjusted returns:

(4) $$CAR_{t_1,t_2} = \sum_{t=t_1}^{t_2} AR_t$$

Where a positive CAR would mean that the portfolio has outperformed the market over the period of time considered, whereas a negative CAR would mean that the stocks in the portfolio show underperformance relative to their already listed peers.

Note that to derive the CAR of the total portfolio, the cumulative abnormal returns of each firm individually could be derived first before merging it over the cross section to calculate the average CAR of all the firms in the portfolio, as is done in this paper.[29] To be able to clearly distinguish the cumulative abnormal return figures of the firms individually and the total portfolio, they will be referred to as CAR and CAAR respectively in the rest of the paper.[30]

While not being able to come to a consensus regarding what method should be used calculate long-term performance, the authors do not show a clear view on what time frame should be considered either. Most of the papers either use a 3- or 5-year interval, or both. Due to the sample

[29] This is done in in order to be able to run regressions for different variables.

[30] Note that the CAAR would have the calculation of equation (4) and CAR is then computed as: $CAR_{t_1,t_2} = \sum_{t=t_1}^{t_2} ar_{it}$

period of 2008-2017 and not wanting to lose many observations, a three-year time frame will be considered. Furthermore, in order to draw a comparison, the stock performances of the companies in the first year after the IPO will also be taken into account (1-year interval).

Another area of focus should be the situation when a company delists during the time interval that is being considered. Firms can delist because of poor performances or when it is acquired by another firm. The literature truncates the returns when a delisting occurs, meaning that there are no more returns recognized in the months after delisting resulting in the fact that the cumulative abnormal returns of the company are equal to the return of the market. This rationale is followed for this analysis.

4.3. Independent variables

In order to compare the short-and long-term results of fintech companies with the financial sector as a whole and test the hypotheses, a dummy variable *DFINTECH* is constructed that takes the value of 1 when the company is considered as fintech and 0 otherwise. As previously mentioned in the Data chapter, the method applied by Dranev et al. (2019) is followed. Companies will be considered as fintech whenever they have the SIC code related to both the finance industry and the technology sector. This means that the company will obtain the value of 1 when they have a SIC code part of Major SIC Group 60-67 or 87-89, as well as SIC code 7371-7374. Following the hypotheses formulated in chapter 2, the sign of the coefficient is expected to be positive in the short-run and negative in the long-run.[31]

Other variables than the company being fintech or not could influence the outcome. Therefore, numerous control variables are included in the analysis that can be divided into three subgroups: firm characteristics, offer characteristics and market characteristics. The rationale for including the control variable and the expected sign of the coefficient based on the literature are explained hereafter for each variable, as well as the way it is computed. In Table 2, an overview of the definition and calculation of all the control variables is then provided, along with their expected coefficients for both the short-term underpricing and long-term cumulative abnormal returns.

[31] In the short-run, the hypothesis is that the underpricing will be higher for fintech companies. The dummy variable would therefore have a positive relationship with the dependent variable, being the initial first day returns. In the long-run, the hypothesis is that the underperformance will be higher for fintech companies. The dummy variable would therefore have a negative relationship with the dependent variable, being the cumulative abnormal returns (CAR's).

The first factor that could have an influence on the outcome and is a characteristic of the firm is the age of the company at the time of the IPO. The studies of Beatty & Ritter (1986) and Barry et al. (1990) both mention that the age of the company has a negative relationship with underpricing as the valuation of younger firms tends to be more uncertain. Additionally, the longer a company exists, the more (historic) information about the company is available. This information on e.g. revenue, earnings and growth is essential in the valuation process and, therefore, reduces uncertainty. Ritter (1991) provides evidence of a positive relationship between company age and long-term stock performance and argues that besides the age of the company being a measure for ex-ante uncertainty, younger firms also tend to be more prone to investor overoptimism as investors all hope to invest as early as possible in high growth companies.

To control for this, the variable *AGE* is constructed and is calculated by taking the natural logarithm of one plus the difference between the year in which the IPO took place and the founding year of the company. Following the literature, the variable is expected to have a negative coefficient in the short run and a positive one in the long run.

Another firm characteristic that could have an influence on the analysis is the size of the company going public. Purnanandam & Swaminathan (2004) and (Brau et al., 2012) both suggest to use the revenue of the company in the fiscal year prior to the IPO as an ex-ante proxy for the size of the firm. One could also use the profit of the firm. However, many IPO firms do not have positive earnings while certainly being firms of considerable size (Purnanandam & Swaminathan, 2004). To control for the size of the firm, the variable *REVENUE* is therefore constructed and is calculated by taking the natural logarithm of the revenue of the company (in thousands of dollars) in the fiscal year prior to the IPO. To control for any missing values, the sample is divided into five subgroups based on the gross proceeds of the IPO. If a company has a missing value for revenue, the mean of the revenues of the companies in its subgroup based on proceeds will be taken as their value for *REVENUE*.[32] As investors encounter less uncertainty during the valuation process of bigger companies, the variable is expected to have a negative coefficient in the short run. Brav & Gompers (1997) mention that the underperformance they found in their analysis is mainly present for smaller firms. The relationship is therefore expected to be positive with the abnormal returns in the long run.

[32] By doing so, the value for revenue of the companies that have missing values will be based on firms of reasonably comparable size.

There are many studies mentioning the effect of the firm being capital backed on the post-IPO performance. This, of course, is also a firm characteristic. Barry et al. (1990) state that the capital markets recognize the monitoring of the firms provided by venture capitalists. The quality of the venture capitalists therefore determines the level of underpricing, which logically follows in a negative relationship between underpricing and firms that are venture-backed by high-quality venture capitalists. The less experienced venture capitalists can be assumed to be of lower quality. They might overestimate their companies and take them public too early. This phenomenon is described as grandstanding by Berlin (1998). As an effect, investors are willing to pay a lower amount for the issued shares of these companies. For the long-run, studies like the ones of Loughran & Ritter (1995) and Brav & Gompers (1997) provide evidence of venture backed firms outperforming non-venture backed firms. On the other hand, the grandstanding phenomenon as stated by Berlin (1998) can have a negative effect on the performances of venture-backed companies in the long run. Berlin adds to this that venture capitalists are subject to using very short time horizons caused by the pressure to bring the company to the stock market. This line of reasoning is underlined by Myers (2017) for the fintech sector. He states that the fintech environment is particularly prone to this kind of "growth-at-all-cost" behavior, which has negative effects on the long run IPO performances. To measure the effect of the firm being venture capital-backed or not, the dummy variable *DVENTURECAP* is constructed. This variable takes the value of 1 whenever the firm going public is venture capital backed, and 0 otherwise. The coefficients are expected to be positive in both the short- and long-run.

Besides the firm-specific characteristics, there are also offer characteristics possible to have an influence on the outcome of the analyses. The first one being the size of the initial public offering, which is naturally measured by the gross proceeds of the IPO. Beatty & Ritter (1986) included this variable in their analysis and provide evidence for it to be an appropriate proxy and show that it has a negative relationship with the initial returns. The rationale they follow is that smaller offerings, on average, are more speculative than larger offerings. The findings of Carter & Manaster (1990) are in line with those of Beatty and Ritter (1986), as they find an inverse relationship between the issue size and the volatility of the initial returns. Jain & Kini (2006), together with Ritter (1991) and Carter et al. (1998), use the proceeds of the public offering to control for the influence of the offer size on the long-run post-IPO performance. They all find that the long-run stock performance improves as the offer size increases, as the larger offers are mostly made by firms that are more established and therefore less prone to risk and uncertainty. The variable *PROCEEDS* is included in the analysis and is calculated by taking the natural logarithm of the IPO gross proceeds in millions of dollars, being the number of shares offered multiplied by the offer price. Following the literature, the coefficient is expected to be negative in the short-run and positive in the long-run.

Another phenomenon that is often mentioned in the literature as something that has an effect on the post-IPO performance of firms going public and could be seen as an offer characteristic is the quality of the underwriter that handles the IPO. As mentioned before in chapter 2, an information asymmetry arises between the issuer of new securities and the investment banker as the underwriter is better informed about the capital market's demand. In order to be compensated for sharing that information with the issuer, underpricing occurs (Baron, 1982). Loughran & Ritter (2004) come up with the changing issuer objective function model which is based on the agency problem between the firm going public and the underwriter. The model predicts that the quality and reputation of the underwriter has a positive relationship with underpricing. The authors state that the reason for this is that issuing companies value underwriters of better quality as they have highly ranked analysts and analyst coverage is getting increasingly important. Additionally, they mention that venture capitalists and executives of the companies going public might receive side payments in order to interfere with the choice of the underwriter. These side payments might result in choosing underwriters that tend to have a reputation for underpricing.[33].

On the other hand, the fact that the underwriter is of higher quality might reduce the ex-ante uncertainty of the issue and, therefore, the underpricing (Carter & Manaster, 1990). Another explanation for a possible negative relationship between underwriter reputation and underpricing is given by Beatty and Ritter (1986). They follow the rationale that in order to maintain their reputation, high quality underwriters assure that they do not leave too much money on the table as this might put off potential customers. This expectation of reputable underwriters to be associated with less short-run underpricing is backed with findings by Carter et al. (1998) and Michaely & Shaw (1994). These studies also find that the long-run underperformance of issuing stocks relative to the market is less severe when the IPOs are handled by more prestigious underwriters. When examining the IPOs of Chinese stocks, Wang et al. (2003) also find that the

[33] Loughran & Ritter (2004) refer to this phenomenon as 'spinning'.

issue being handled by underwriters with higher reputations has a positive effect on the three-year post-IPO performance. In order to control for the effect that the underwriter being of high quality has on the short-run underpricing and long-run performance, the dummy variable *DHQ_UNDRW* is created. As public offerings tend to be handled by more than one underwriter, the variable contains 1 if one of the underwriters of the IPO is of high quality, and 0 otherwise. The underwriters are classified as 'high quality' when they have a reputation of 8.0 or higher based on the rankings of Griffin et al. (2014).[34] The coefficients are expected to be negative for the short-run initial returns and positive for the long-run abnormal returns.

Control variables that are used to control for macro-economic market characteristics are the interest rate and the market index returns. To control for the interest rate, the variable *INTERESTRATE* is constructed and is calculated as the average interest rate over the day before the IPO and the day of the issue itself. For the companies in the American sample the US Federal Funds rate is used, whereas the Euro Interbank Offered Rate is used for the European companies. Brau et al. (2003) provide some rationales on the effect that the interest rate has on the IPO activity. In periods of high interest rates, highly leveraged firms might prefer external equity over the use of debt when external financing is required. Periods of higher interest rates might therefore increase the IPO activity. This line of reasoning is firstly presented by Myers & Majluf (1984) and is called the pecking order hypothesis. The literature does not provide much insights on what the effect of the interest rate on the initial stock returns and long-run stock performance would be. However, Bairagi & Dimovski (2011) find a significant positive relationship between the 10-year US treasury interest rates and the level of underpricing. In the short-run, the relationship is therefore expected to be positive. For the long-run, there is not necessarily a predicted sign for the coefficient.

To control for the market index return, the variable *INDEX_REGION* and *INDEX_WORLD* are computed and calculated by taking the buy-and-hold returns of the value-weighted index over the 15 trading days prior to the IPO, as also used in Loughran & McDonald (2013) and Carter et al. (1998). The *INDEX_WORLD* is used in the regression for the total sample and is calculated based on the MSCI World index. The *INDEX_REGION* variable is used in the regressions for the separate European and American sample. For the companies from the United States, the NASDAQ Composite index is used. For the European companies, the 15 trading days buy-and-

[34] This ranking is chosen as it contains both European and American underwriters, which is of course essential for the analysis.

hold profits are calculated for the MSCI Europe index. Loughran & McDonald (2013) find a positive relationship between the prior 15-day Nasdaq returns and the first-day initial returns. Cassia et al., (2004) find a similar relationship. However, they use the index returns of 100 days prior the IPO. The coefficient is therefore expected to be positive in the short-run. There isn't necessarily a predicted sign for this market characteristic coefficient in the long-run as well, as the literature does not provide any convincing evidence or rationale on it.

As previously mentioned, firms might delist due to poor performances or when acquired by another firm. Fama & French (2004) mention that over the period of 1980-2001 the amount of firms that delist has increased sharply and argue that this is due to lower cost of equity. This causes the firms that go public to be less profitable and rather high-growth firms. Companies that delist early can cause noise in the data and in order to control for that, the dummy variable *DDELIST_36* is created. [35] The variable takes the value of 1 if the company delists in the 36 months after the IPO, and 0 otherwise. Due to the fact that both the one- and three-year CAR's will be used as dependent variables in the regressions, two different dummy variables to control for the effect of delisting could have been created. However, as a neglectable amount of firms in the sample turn out to delist in the first year after the IPO, it is not relevant to construct a dummy variable that controls for that. Fama & French (2004) state that the decline in survival rates is mainly due to poor performances. Therefore, the coefficients are expected to be negative for both the short- and long-run. Table 2 below provides on overview of the definition and calculation of all the control variables previously discussed, along with their expected coefficients on both the short-run underpricing and the long-run cumulative abnormal returns.

[35] This variable is naturally only included in the long-run analyses.

TABLE 2. CONTROL VARIABLES

Control Variable	**Expected sign**		**Definition**
	Short-run	**Long-run**	
Firm characteristics			
AGE	-	+	Natural logarithm of the difference between the year of the IPO and the founding year of the company.
REVENUE	-	+	Natural logarithm of the revenue of the company (in thousands of dollars) in the fiscal year prior to the year of the IPO
DVENTCAP	+	+	Variable takes the value of 1 whenever the firm going public is venture capital backed, and 0 otherwise.
Offer characteristics			
PROCEEDS	-	+	Natural logarithm of the IPO gross proceeds (in millions of dollars), being the number of shares offered multiplied by the offer price
DHQ_UNDRW	-	+	Variable that contains 1 if one of the underwriters of the IPO is of high quality, and 0 otherwise. Underwriters are classified as 'high quality' if they have a reputation of 8.0 or higher in Griffin et al. (2014).
Market Characteristics			
INTERESTRATE	+		Average interest rate over the day before the IPO and the day of the issue itself. For the companies in the American sample the US Federal Funds rate is used, whereas the Euro Interbank Offered Rate is used for the European companies
INDEX_REGION	+		Buy-and-hold returns of the value-weighted index over the 15 trading days prior to the IPO. The NASDAQ Composite index is used for the US sample, whereas for the European sample the MSCI Europe index is used.
INDEX_WORLD	+		Buy-and-hold returns of the value-weighted MSCI World index over the 15 trading days prior to the IPO
Delisting variable			
DDELIST_36	-	-	Variable takes the value of 1 if the company delists in the first 36 months after the IPO respectively, and 0 otherwise.

Definition of the control variables by category and their corresponding expected coefficients on both the short- and long-run.

4.4. Descriptive statistics

Table 3 provides an overview of the descriptive statistics of all the control variables used in the analysis, for both the total sample and for Europe and the United States separated. As the short-term sample contains the most companies, that sample is used and displayed below. The descriptive statistics of the long-term sample can be found in Appendix A. For the completeness, the delisting variable of the table of the long-run sample is included in the table below.

TABLE 3. DESCRIPTIVE STATISTICS OF CONTROL VARIABLES

VARIABLES	(1) mean	(2) median	(3) min	(4) max	(5) sd	(6) N
Firm Characteristics						
Age (in years)	13.62	6	0	296	24.91	1,287
Europe	14.62	7	0	296	27.21	688
United States	12.47	6	0	159	21.93	599
REVENUE	11.15	11.56	0	18.18	2.697	1,287
Europe	11.00	11.36	1.386	18.18	2.977	688
United States	11.23	11.39	0	17.24	2.330	599
DVENTCAP	0.184				0.388	1,287
Europe	0.0683					688
United States	0.317				0.466	599
Offer characteristics						
PROCEEDS	4.442	4.605	-7.567	13.40	1.813	1,287
Europe	4.215	4.444	-7.567	13.40	2.185	688
United States	4.702	4.687	-0.693	9.791	1.207	599
DHQ_UNDRW	0.429				0.495	1,287
Europe	0.272					688
United States	0.609				0.488	599
Market Characteristics						
INDEX*	0.00731	0.00958	-0.229	0.114	0.0319	1,287
Europe	0.00277	0.00213	-0.240	0.163	0.0384	688
United States	0.0137	0.0163	-0.143	0.146	0.0385	599
INTEREST						
Europe	0.00304	0.00015	-0.00544	0.0496	0.0104	688
United States	0.00609	0.00145	0.000450	0.0345	0.00792	599
Delisting variable						
DDELIST_36	0.0923				0.290	899
Europe	0.110				0.314	526
United States	0.0670				0.250	373

Data on IPOs for 2008-2020. The elaborations and calculations of the independent variables can be found in chapter 4.2. For the dummy variables, only the mean and the standard deviation are presented. The means represent what percentage of the observations have the value of 1. The data is retrieved from Thomson One, Eikon Datastream and Zephyr.

*MSCI World index is used for the total sample, Nasdaq composite and MSCI Europe for US and EU respectively.

All the variables have 1287 observations and 688 and 599 for Europe and the United States respectively, which corresponds with the size of the total sample presented in Table 1. This implies that there are no missing values for all of the variables.[36] [37] The variables for total IPO proceeds and revenue are already logged, but not for the age of the companies. This is done deliberately in order to give a clear overview on the age that companies are when going public. On average, the firms from Europe in our sample are on average older when going public than their US equivalents, which is in line with the literature provided in chapter 2. Another striking difference between the United States and Europe is the number of firms that are venture capital backed, which is significantly higher in the US. The reason for this is that the venture capital market of the United States is much more developed and more heavily invested in early-stage ventures and high-technology industries than the European venture capital market. This rationale is stated by Black & Gilson (1998) when comparing Germany and the United States. In the table below, the correlation matrix of the independent variables is displayed. As the short-term sample contains the most companies and will therefore yield the most reliable results, this one is again displayed below. The correlation matrix of the long-run sample can be found in Appendix B. As the correlations do not differ that much between the samples consisting of firms from Europe and the United States, a separation between the two is not relevant to be displayed in the thesis or the Appendix. Note that high values in the correlation coefficients indicate a predictive relationship rather than a causal relationship.

TABLE 4. CORRELATION MATRIX: TOTAL SAMPLE (SHORT-RUN)

Variables	**(1)**	**(2)**	**(3)**	**(4)**	**(5)**	**(6)**	**(7)**	**(8)**	**(9)**
(1) DFINTECH	**1.000**								
(2) AGE	**0.084**	**1.000**							
(3) REVENUE	**0.047**	**0.120**	**1.000**						
(4) DVENTCAP	**0.083**	**0.067**	**-0.123**	**1.000**					
(5) PROCEEDS	**0.025**	**0.013**	**0.555**	**0.017**	**1.000**				
(6) DHQ_UNDRW	**0.070**	**0.051**	**0.373**	**0.200**	**0.536**	**1.000**			
(7) INTERESTRATE	**-0.086**	**0.004**	**-0.072**	**0.126**	**-0.163**	**0.024**	**1.000**		
(8) INDEX_REGION	**-0.027**	**-0.030**	**0.023**	**0.080**	**0.091**	**0.085**	**-0.051**	**1.000**	
(9) INDEX_WORLD	**-0.042**	**-0.025**	**0.034**	**0.016**	**0.087**	**0.049**	**-0.096**	**0.908**	**1.000**

Pearson's correlation coefficients for all the variables used in the short-term analysis. Data on IPOs between 2008-2020 for firms from both Europe and the United States, retrieved from Thompson One, Eikon and Zephyr.

[36] Note that for *REVENUE* there were some missing values. As mentioned before, these have been treated by dividing the sample into five subgroups based on the gross proceeds of the IPO and substituting the mean of the revenues of the companies in the subgroup of which the firm that had a missing value is part of.

[37] The delisting variable of course has less observations, as the long-term sample is smaller. For this variable, the total observations also correspond with the size of the sample presented in Table 1.

When analyzing the table for any relationships between fintech firms and the other variables, none of the correlation coefficients is noteworthily high. As can be seen in Appendix B, this is also not the case for the delisting variable. One could have expected a negative relationship between *DFINTECH* and *AGE*, as fintech is a relatively new market and Karlis (2008) mentioned that tech or internet companies conducting IPOs are relatively young in terms of age. However, a correlation coefficient of 0.084 shows that this is not the case for our sample.

There are some control variables that seem to be relatively high correlated with each other. First of all, there is a high correlation between the revenue in the fiscal year prior to the IPO and the gross proceeds of the issue. This is something that could have been expected, as revenue is used as a proxy for firm size and bigger firms are naturally able to attract more money through an IPO than smaller firms. Furthermore, being of greater size also enables these firms to attract more prestigious underwriters (Megginson & Weiss, 1991), which explains the correlation of 0.373 between the high-quality underwriter dummy and the revenue variable. Higher correlation coefficients between the gross proceeds of the IPO and the underwriter being of higher quality is also something that could have been expected, as more prestigious underwriters might have the quality of increasing the proceeds. However, this higher correlation might also be due to the relationship between the size of the firm and the gross proceeds. As mentioned before, bigger firms generate more money through IPOs and are able to pick underwriters of higher quality, so these IPOs of higher gross proceeds are naturally handled by more prestigious underwriters. Bearing this in mind, an analysis with interaction terms included for these three variables are conducted as robustness checks to see if the coefficients and the total model improve.

High correlations between independent variables could also be indicating signs of multicollinearity. Therefore, this will be tested using the variance inflation factor (VIF) test prior to conducting the analyses. The rule of thumb states that only when there are one or more variables that have a value of the VIF higher than 10, multicollinearity could be of influence on the analysis (O'Brien, 2007).

5. Results

In this chapter, the hypotheses drawn in chapter 2 are tested by discussing and analyzing the outcomes of the regression analyses that were outlined in chapter 4. Section 5.1 illustrates the results for the short-run analysis and is followed by the results of the long-run analysis in chapter 5.2. Before discussing the regression analyses, the initial first-day returns and the cumulative abnormal returns are analyzed in order to draw some first impressions on these values.

5.1. Short-run underpricing

In Figure 1, the total number of IPOs per year from 2008 till 2020 are displayed, as well as how many of those were by companies classified as fintech. Additionally, the average first-day returns per year are plotted in the graph for both the total sample and fintech companies only. In Appendix C, the corresponding t-statistics when tested if these means are statically different from 0 can be found. Figure 1 shows that the level of underpricing of the total sample, although reasonably volatile, has been fairly constant over the years. Except for 2008, these initial returns are all statistically significant on the 1% level, as can be seen in table C1. The fact that 2008 shows some odd results in terms of significance of the underpricing level is related to the lower volume of IPOs. This is of course due to the financial crisis and is in line with the literature.

Figure 1 shows that for almost all years the underpricing level of the fintech companies has been higher than that of the total sample, which is in line with hypothesis *H1*. The only year that the average initial return is lower for the fintech companies is 2015. However, as can be seen in the graph, the difference is neglectable. Table C1 shows that many of these average first-day returns are of statistical significance at the 1% or 5% level.

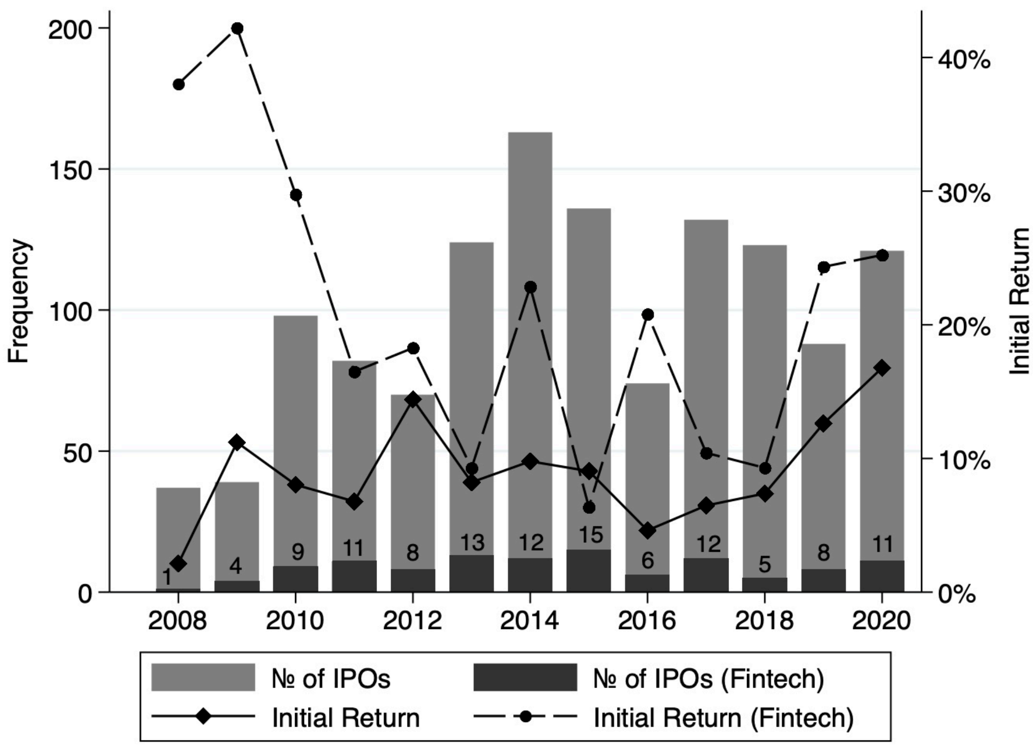
The average initial returns of fintech companies have been strikingly high in 2008 and 2009 with 38% and 42.2% respectively.[38] This is an interesting result, as the underpricing levels have generally been really low for the years after the financial crisis, something which is also noticeable when looking at the initial returns of the total sample in those years. This tendency of low first-day returns and volume of IPOs in the years after the crisis is also present in the literature; Ritter (2021) reports a mean first-day return of 5.7% in 2008 for firms from the United

[38] The remark has to be made that these initial returns are based one single firm for 2008, while the average return for 2009 is based on four companies (see Figure 1).

States,[39] while the amount of firms going public in Germany declined to one of the lowest levels of the past 40 years (Ritter, 2021). The fact that fintech firms experience such high levels of underpricing in the years after the financial crisis could be due to the fact that it changed the people's perception about the banks and the financial services industry and as a consequence, one started looking for alternatives (Arner et al., 2016).

FIGURE 1. TOTAL NUMBER OF IPOS AND INITIAL RETURN BY YEAR

Volume of IPOs and mean first-day initial returns per year for both the total sample and fintech firms only. Data on IPOs from financial firms from the United States and Europe between 2008-2020, retrieved form Thompson One, Eikon Datastream and Zephyr.



The tendency of fintech firms to show higher levels of underpricing displayed in figure 1 is backed by table C2 of Appendix C. For the period considered, the firms classified as fintech have a higher mean first-day initial return than non-fintech firms, significant on a 99% confidence interval. Where non-fintech firms have an average first-day return of 7.3%, fintech firms show an average level of underpricing of 13.6%. These findings are in line with hypothesis *H1*, which will hereafter be tested further by conducting the regression analyses.

[39] The sample contains IPOs with an offer price of at least $5.00, excluding ADRs, unit offers, closed-end funds, REITs, natural resource limited partnerships, small best effort offers, banks and S&Ls, and stocks not listed on the Amex, NYSE and NASDAQ.

5.1.1. Cross-sectional regressions

As mentioned in chapter 4.1, outliers that could potentially have an influence on the regression analyses are indicated upfront using Cook's distance and DFITS. All the cases that have values of COOKSD and DFITS above the threshold set by the rule of thumb are normally excluded from the analysis.[40] However, adhering to the rule of thumb did not improve the model in this particular case. Visual inspection and a trial-and-error process eventually led to excluding all the cases above the thresholds of COOKSD > 0.01 and DFITS > 0.3, resulting in eliminating only 14 influential cases and an eventual sample of 1273 observations. As Table 5 showed some high correlations between certain variables, a variance inflation factor (VIF) test is conducted in order to indicate multicollinearity, of which the results can be found in Appendix D. As the rule of thumb states that only when there are variables with VIF statistics above 10 the analysis can be influenced and all the variables have values below 2,[41] none of the variables need to be excluded from the model. Another assumption of the OLS regression which is necessary to test is if the error terms have constant variance. Various tests for heteroskedasticity are therefore conducted of which the outcomes can also be found in Appendix D. As these tests indicate signs of heteroskedasticity, using robust standard errors in the analysis to control for the potential influence of biased standard errors will most probably improve the model. As the estimates are of lower variance and the significance of the coefficients improve when controlling for heteroskedasticity, the short-term analyses are conducted using robust standard errors.

The results of the regression analyses can be found in Table 5. Model 1 regresses the fintech dummy variable against the initial returns. From model 2 to 7 onwards, control variables are added to the model to see if this improves the model and/or changes the significance and coefficients of the fintech dummy. Model 8 runs the regressions with all the variables, including a region dummy that controls for the companies being in either the United States or Europe. In model 9, a year dummy that controls for the year in which the issue took place is added to the analysis. The most important finding is that the coefficient of *DFINTECH* is positive and significant at a 99% confidence interval in all the models, showing that the firm being classified

[40] For this analysis the rule of thumb resulted in the following threshold for Cook's distance: 4 / (1287-7-1) = 0.0031274. For DFITS the threshold equals 2 * √ (7/1287) = 0.14749.

[41] Test statistics of the VIF test can be found in table D1.

as fintech increases the level of underpricing. The coefficient of *DFINTECH* in model 9 indicates that, holding all the other predicters in the model constant, the initial returns of fintech firms are 5% higher than that of non-fintech firms. The R-squared equals .269 when including all the control variables and adding the region and year dummy to the analysis. This means that the independent variables included in model 9 explain 26.9% of the variance in the initial returns. The model improves significantly when adding the variable that controls for the firms being venture capital backed or not. Furthermore, its coefficient is constantly positive with a higher value than the fintech dummy in all of the models it is included in, while also being statistically significant at the 1% level.

TABLE 5. OLS REGRESSION ON INITIAL RETURNS

	(1) IR	(2) IR	(3) IR	(4) IR	(5) IR	(6) IR	(7) IR	(8) IR	(9) IR
DFINTECH	.063***	.06***	.059***	.049***	.049***	.048***	.05***	.053***	.05***
	(.016)	(.016)	(.016)	(.016)	(.016)	(.016)	(.016)	(.016)	(.016)
AGE		.006**	.006*	.004	.004	.004	.004	.004	.005
		(.003)	(.003)	(.003)	(.003)	(.003)	(.003)	(.003)	(.003)
REVENUE			.002	.004**	.004**	.003*	.003*	.003*	.002
			(.002)	(.002)	(.002)	(.002)	(.002)	(.002)	(.002)
DVENTCAP				.08***	.08***	.074***	.074***	.063***	.059***
				(.016)	(.016)	(.016)	(.016)	(.016)	(.016)
PROCEEDS					0	-.003	-.003	-.003	-.003
					(.003)	(.003)	(.003)	(.003)	(.003)
DHQ_UNDRW						.022**	.022**	.012	.012
						(.01)	(.01)	(.01)	(.01)
INDEX_WORLD							.449***	.432***	.324***
							(.155)	(.154)	(.153)
_cons	.073***	.062***	.037**	.008	.008	.019	.017		
	(.005)	(.006)	(.017)	(.018)	(.018)	(.019)	(.019)		
Observations	1273	1273	1273	1273	1273	1273	1273	1273	1273
R-squared	.012	.014	.016	.052	.052	.055	.063	.248	.269
Region dummy	NO	NO	NO	NO	NO	NO	NO	YES	YES
Year dummy	NO	NO	NO	NO	NO	NO	NO	NO	YES

Data on IPOs of financial firms between 2008-2020 from the United States and Europe. The dependent variables are the initial returns, calculated by taking the natural logarithm of the closing stock price after 1 trading day divided by the offer price. Elaborations and calculations of the independent variables can be found in chapter 4.2.The data is retrieved from Thomson One, Eikon Datastream and Zephyr.

Robust standard errors are in parentheses. *** p<.01, ** p<.05, * p<.1.

This indicates that firms that are backed by venture capital experience higher level of underpricing. These findings are in line with those of Lee & Wahal (2004), who provide evidence of venture capital backed IPOs to experience larger first-day initial returns. Another outcome that is worth mentioning is that of the variable that controls for the market index in the 15 days prior the IPO. The coefficient being very high and significant at a 99% confidence interval shows a strong positive relationship between the initial returns and the returns of the MSCI World index in the 15 days before the IPO. While using different indices, Loughran & McDonald (2013) and Cassia et al. (2004) find similar evidence in their studies. The fact that both the dummy variables for fintech firms and for firms that are venture capital backed are significantly positive might indicate that the significant positive relationship between the initial returns and firms being classified as fintech might be due to many of the fintech firms being venture capital backed. However, the correlation coefficient for the relationship between *DFINTECH* and *DVENTCAP* in Table 4 indicates that this is not the case. As previously mentioned, the variables that control for the revenue, proceeds and the underwriter being of high quality experience high correlation with each other and will therefore be included as interaction terms as a robustness check for model 9. The outcome is displayed in Table 6. The interaction terms are added seperately to the model first in order to see the impact of adding them to the analysis. When doing so, none of the interaction terms show significant results and there are not any noteworthy changes in the other coefficients or the total explanatory power of the model as well. However, some changes occur when adding them all together in model 5. The interaction term that multiplies the natural logarithm of the IPO's gross proceeds with the variable that controls for high quality underwriters shows a small positive coefficient that is significant at the 10% level. This indicates that firms with higher gross proceeds are strengthening the effect that the IPO being handled by a high quality underwriter has on the level of underpricing. Additionally, when including all of the interaction terms in the analysis, the relationship between revenue and initial returns becomes significant when considering a 10% confidence interval, while also slightly increasing the coefficient of the venture capital dummy variable. The positive relationship between revenue and initial returns is an interisting founding, as it is used to control for the size of the firm. Investors are expected to enounter less uncertainty during the valuation of bigger companies, which should result in lower levels of underpricing (Purnanandam & Swaminathan, 2004). The explanatory power of the total analysis does not change much either, as the r-squared increases from 26.9% to 27.1%.

TABLE 6. OLS REGRESSION ON INITIAL RETURNS INCLUDING INTERACTION TERMS

	(1) IR	(2) IR	(3) IR	(4) IR	(5) IR
DFINTECH	.05***	.051***	.05***	.05***	.05***
	(.016)	(.016)	(.016)	(.016)	(.016)
AGE	.005	.005*	.004	.005	.004
	(.003)	(.003)	(.003)	(.003)	(.003)
REVENUE	.002	.004	.002	.002	.008*
	(.002)	(.004)	(.002)	(.002)	(.005)
DVENTCAP	.059***	.058***	.062***	.059***	.063***
	(.016)	(.016)	(.016)	(.016)	(.016)
PROCEEDS	-.003	.001	-.004	-.002	.008
	(.003)	(.007)	(.003)	(.003)	(.009)
DHQ_UNDRW	.012	.014	-.044	.001	-.077
	(.011)	(.011)	(.04)	(.043)	(.058)
INDEX_WORLD	.324**	.322**	.32**	.326**	.311**
	(.153)	(.153)	(.152)	(.153)	(.153)
PROCEEDS#REVENUE		0			-.001
		(.001)			(.001)
DHQ_UNDRW#PROCEEDS			.01		.017*
			(.007)		(.009)
DHQ_UNDRW#REVENUE				.001	0
				(.004)	(.004)
Observations	1273	1273	1273	1273	1273
R-squared	.269	.269	.27	.269	.271
Region dummy	YES	YES	YES	YES	YES
Year dummy	YES	YES	YES	YES	YES

Data on IPOs of financial firms between 2008-2020 from the United States and Europe. The dependent variables are the initial returns, calculated by taking the natural logarithm of the closing stock price after 1 trading day divided by the offer price. Elaborations and calculations of the independent variables can be found in chapter 4.2. The data is retrieved from Thomson One, Eikon Datastream and Zephyr.

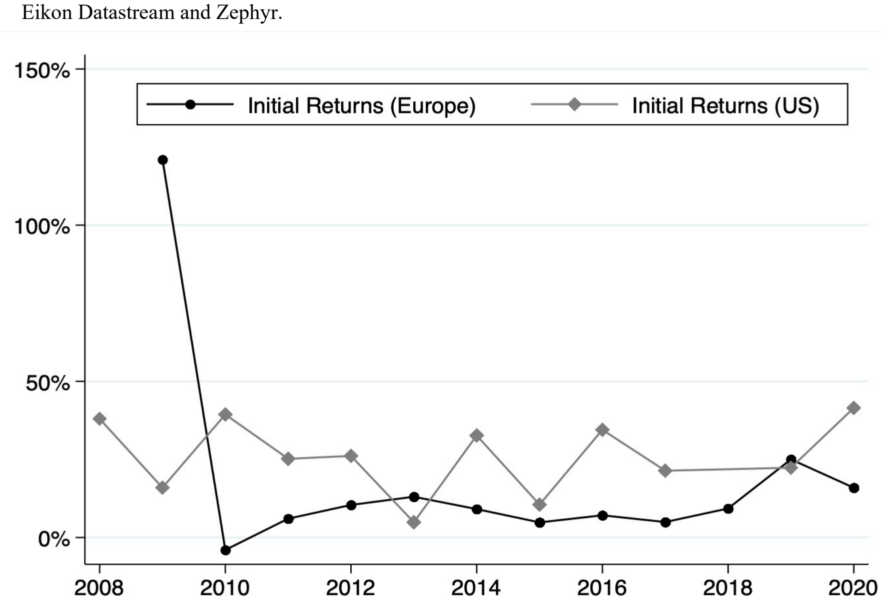
However, the most relevant finding is that none of the interaction terms have an effect on the coefficients or significance of the fintech variable when included in the analysis. The coefficient of *DFINTECH* is positive in all the models and significant at the 1% level, also when adding the interaction terms to the analysis. Hypothesis *H1* is therefore supported, as these results show that the level of underpricing is higher for fintech firms when compared to the financial industry as a whole. Following the literature outlined before coming to the hypothesis, this is probably due to the fact that firms from the fintech industry are characterized by higher grades of uncertainty. First of all, the industry has a very innovative character and is still at its preliminary stage, increasing the unpredictability. Furthermore, fintech firms are vulnerable to financial distress as their cash flows tend to be highly volatile and their assets are mainly intangible (Kim et al., 2008). In addition, Ryu & Ko (2020) point out that the transaction and activities of fintech companies tend to be even more complicated than general internet companies. As the latter are already known to be more prone to underpricing (Karlis, 2008), the higher levels of underpricing for fintech firms are in line with the literature.

5.1.2. Comparing Europe and the United States

The initial returns of fintech firms tend to be higher in the United States than in Europe when plotted over the years in Figure 2. Despite a major peak in 2009,[42] the level of underpricing for fintech companies in Europe is below that of the United States, following a reasonably constant trend. This tendency is underlined when looking at the differences between the two regions in Table C2; while the average initial return for fintech firms equals 9.9% in Europe, its American equivalents experience an average underpricing of 18.3%. These means are both significant at the 1% level when tested if they statistically differ from 0. This indicates that the effect that fintech companies experience higher levels of underpricing when compared to the financial sector as a whole, as shown in chapter 5.1.1., might be stronger in the United States than in Europe. In other words, these first impressions are in line with hypothesis *H1a*.

FIGURE 2. INITIAL RETURN OF FINTECH COMPANIES BY YEAR

Average first-day initial returns per year for fintech firms from Europe and the United States. Data on IPOs of financial firms from the United States and Europe between 2008-2020, retrieved form Thompson One, Eikon Datastream and Zephyr.



[42] Of the 4 firms classified as fintech with an IPO in 2009, only one them is from Europe. This peak is therefore due to only one firm, Flatex Holding AG, reporting an initial first-day return of 120.9%.

In order to test if hypothesis H1a is supported, an interaction term between the fintech variable and the variable that controls for the firms being either in the United States or Europe is added to model 9 of Table 5. The outcome is displayed in Table 7 below. The coefficient of the interaction term being negative indicates that the effect of higher underpricing levels for fintech firms is stronger in the United States than in Europe, which is in line with hypothesis *H1a*. The initial first-day returns are 3.6% higher in the United States than in Europe for fintech firms that conducted an IPO between 2008 and 2020.

TABLE 7. OLS REGRESSION ON INITIAL RETURNS INCLUDING INTERACTION TERM

	(1)	(2)
	IR	IR
DFINTECH	.05***	.071***
	(.016)	(.027)
AGE	.005	.005*
	(.003)	(.003)
REVENUE	.002	.002
	(.002)	(.002)
DVENTCAP	.059***	.057***
	(.016)	(.016)
PROCEEDS	-.003	-.003
	(.003)	(.003)
DHQ_UNDRW	.012	.011
	(.011)	(.011)
INDEX_WORLD	.324**	.323**
	(.153)	(.152)
1.REGION (EU)	.083***	.087***
	(.032)	(.032)
2.REGION (US)	.107***	.108***
	(.032)	(.032)
1bn.REGION#1.DFINTECH		-.036
		(.032)
Observations	1273	1273
R-squared	.269	.269
Region dummy	YES	YES
Year dummy	YES	YES

Data on IPOs of financial firms between 2008-2020 from the United States and Europe. The dependent variables are the initial returns, calculated by taking the natural logarithm of the closing stock price after 1 trading day divided by the offer price. Elaborations and calculations of the independent variables can be found in chapter 4.2.The data is retrieved from Thomson One, Eikon Datastream and Zephyr.

Robust standard errors are in parentheses. *** p<.01, ** p<.05, * p<.1.

However, this might be due to the fact that underpricing levels are generally higher in the United States than in Europe, something which was implied by Figure 2 and underlined by the coefficients of the region dummy. While both being significant at the 1% level, the firms from the United States experience higher initial returns. Including the interaction term in the analysis also causes the coefficient of the fintech variable to increase, while maintaining its significance. As mentioned before, regressions will also be conducted on the sample divided by region in order to see the differences in the complete model. The outcome of the total regression results of the two different samples split by region are combined in table 7. Only the regression models with all the variables included, both with and without a dummy variable that controls for the year when the IPO occurred, are displayed in the table.[43] The complete regression models can both be found in Appendix E. When looking at the results of regression model 2 and 4 in table 7, the coefficient of the fintech dummy is higher for the US sample than that of the EU sample, which is consistent with the findings in table 7. While the coefficient in model 2 is also significant at the 5% level, both of them are significant when considering a 90% confidence interval. The results of the regression analysis of the total sample displayed in Table 5 showed that the coefficient of the dummy variable that controls for the firm being venture capital backed or not is constantly positive with a higher value than the fintech dummy. Table 7 shows that this effect is mainly present for firms from the United States, as the variable is only significant in model 3 and 4. When looking at the total regression of model 4, displayed in table E2 of Appendix E, it becomes clear that including this variable in the analysis has an influence on the relationship between the firm being fintech and the level of underpricing. While still being significant at the 1% level before, the coefficient of *DFINTECH* remains only significant at the 10% level and drops from .074 to .048 after adding *DVENTCAP* to the analysis. The overall explanatory power of the model however improves as the R-squared increases to 7.9%. When comparing both of the R-squared statistics it strikes that the US model is superior in terms of explanatory power. The independent variables included in the model explain 35.1% of the total variance in first-day initial returns, which is by far the highest of all the regressions conducted on short-term underpricing.

[43] The R-squared of the models displayed in table 7 show that adding the variable that controls for the year that the IPO took place increases the explanatory power of the analysis significantly.

TABLE 8. OLS REGRESSIONS ON INITIAL RETURNS

	(1) (IR) (EU)	(2) IR (EU)	(3) IR (US)	(4) IR (US)
DFINTECH	.046**	.042**	.041	.053*
	(0.19)	(.019)	(.028)	(.027)
Firm Characteristics				
AGE	0	.001	.015***	.016***
	(.003)	(.004)	(.005)	(.005)
REVENUE	.002)	.001	.003	.002
	(.002)	(.002)	(.004)	(.004)
DVENTCAP	-.005	-.009	.094***	.086***
	(.024)	(.025)	(.02)	(.02)
Offer characteristics				
PROCEEDS	-.009**	-.007**	.028***	.028***
	(.003)	(.003)	(.008)	(.008)
DHQ_UNDRW	.012	.01	-.018	-.021
	(.12)	(.012)	(.018)	(.02)
Market characteristics				
INDEX_REGION	.132	.1	.424**	.286
	(.133)	(.138)	(.207)	(.217)
INTERESTRATE	-.972	-.844	-1.049	-1.037
	(676)	(3.564)	(.98)	(4.028)
_cons	-0.67***		-.113***	
	(.023)		(.041)	
Observations	683	683	590	590
R-squared	.028	.192	.109	.351
Year Dummy	NO	YES	NO	YES

Data on IPOs of financial firms between 2008-2020 from the United States and Europe. The dependent variables are the initial returns by region, calculated by taking the natural logarithm of the closing stock price after 1 trading day divided by the offer price. Elaborations and calculations of the independent variables can be found in chapter 4.2. The data is retrieved from Thomson One, Eikon Datastream and Zephyr.
Robust standard errors are in parentheses. *** p<.01, ** p<.05, * p<.1.

As mentioned before, adding the interaction terms to the analysis indicated that the effect of higher first-day initial returns of fintech companies is higher in the United States than in Europe. Furthermore, dividing the sample showed that the relationship between the fintech dummy and the level of underpricing is significantly positive when considering a 90% confidence interval for both the European and American analysis. As the coefficient being higher in the United States confirms the findings of the model including the interaction term between the fintech variable and the region dummy, it can be concluded that these findings are in line with hypothesis *H1a*. These higher level of underpricing for fintech firms in the US were expected, as there are more listing requirements for firms to go public in Europe than there are in the United States (Ritter, 2003). As a consequence, it would be easier for firms that do not necessarily have outstanding financials to go public in the United States. This causes the grade of uncertainty of fintech firms that conduct an IPO to be higher. Furthermore, underwriters from the United States are more sympathetic to taking risky companies to the public market due to the smaller legal risk they encounter compared to their European equivalents (Van der Groot, 2003). However, it should be noted that the negative coefficient of the interaction term was not significant and, despite being slightly higher in the United States, the difference between the coefficients of the fintech variable when dividing the sample by region is very small. Furthermore, the European coefficient is significant at the 5% level, while the coefficient of the analysis containing firms from the United States is only statistically significant when considering a 90% confidence interval. It could therefore be said that the results do not show a clear and significant difference in the magnitude of the effect. Nevertheless, it is clear that hypothesis H1 is also supported when dividing the sample into regions and running separate regression analysis. Firms that are classified as fintech show higher levels of underpricing than firms from the financial sector as a whole when considering IPOs between 2008-2020 from the United States and Europe.

5.2. *Long-run underperformance*

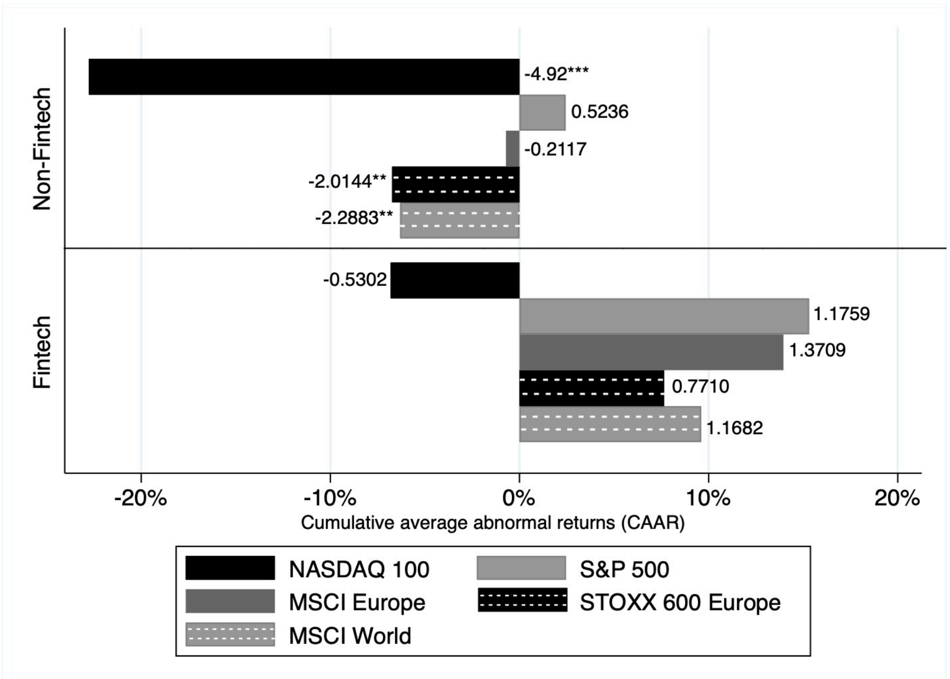
In order to draw some first impressions on the long-run stock performances of non-fintech and fintech companies and their differences, the cumulative average abnormal returns (CAAR) of the companies that belong to these groups are displayed per index used as the benchmark returns in figure 3, along with their corresponding t-values. The latter can be found in full in Appendix C, as well as the t-statistics of the equal-weighted indices used as benchmarks. What immediately stands out is that the returns of the fintech companies are higher than that of the non-fintech companies, which implies results that go against hypothesis *H2*. However, despite being higher, the CAAR's of the fintech companies are all not significant when tested if they statistically differ from 0. This pattern is also present when looking at the equal-weighted indices in Table C4. Furthermore, while showing underperformance relative to the value-weighted NASDAQ-100 index, the fintech firms even outperform the equal-weighted equivalent of the index representing the 100 most traded companies on the NASDAQ.

The companies not classified as fintech on the other hand do show underperformance levels that are significant at the 1% and 5% level. The non-fintech companies from the United States underperform relative to the NASDAQ-100 by 22.8%, while the European equivalents are outperformed by the STOXX 600 Europe by 6.8%. This tendency of fintech firms to perform better than the non-fintech firms included in the sample is also present when looking at a period of 1 year after the IPO in Table C5. The European fintech firms actually show positive cumulative average abnormal returns that are statistically significant when taking a 5% confidence interval into account. However, all of the return values tend to be higher when looking at a 12-monhts post-IPO time frame. These results are in line with the literature, as it takes some time for the stock prices to return to their fundamental value after drifting away from it in the short-run (Bollerslev & Hodrick, 1992).

Figure 3 and the CAAR values displayed in Appendix C underline the essence of using different indices as benchmarks. The cumulative abnormal returns experience major changes when computed with another index that represents the market return. Even when only using the equal-weighted index instead of the value-weighted one, the returns alter significantly. Because of this, hypothesis *H1* stating that fintech firms show higher levels of underperformance will also be considered during the comparison between Europe and the United States and as a result, conclusions on that hypothesis will only be drawn at the end of the entire chapter.

FIGURE 3. CAAR PER INDEX (NON-FINTECH VS FINTECH)

Cumulative average abnormal returns (CAAR) per index used as benchmark return along with their corresponding t-statistics when tested if the means are statistically different from 0. The CAAR's are calculated over a 36-month time frame and the indices used are all value-weighted. Naturally, the CAAR's with indices form the United States used as benchmark only contain firms from the United States, while the European ones only contain firms from Europe. Data on IPOs of financial firms from the United States and Europe between 2008 and 2017, retrieved from Thomson One, Eikon Datastream and Zephyr.
*** p<.01, ** p<.05, * p<.1.



5.2.1. Cross-sectional regressions

First of all, regression analyses are conducted using all the firms present in the sample, both from Europe and the United States. In order to ensure that the market return used for calculating the cumulative abnormal returns is relevant for both markets, the MSCI World index is the index that is being considered as the benchmark. Just as the short-term regression analysis, outliers that could potentially have an influence on the analysis are indicated up front using Cook's distance and DFITS. For the long-run analyses, adhering to the rule of thumb for both the measurement tools turned out to result in the biggest improvement of the models.[44] The outcome of the variance inflation factor (VIF) tests and the tests conducted on heteroskedasticity can be found in Appendix D. As all of the variables have VIF-statistics that are below 2, they all remain included in the analysis. The tests on heteroskedasticity do not show significant signs of the latter being present in the analysis. Furthermore, using robust standard errors did not seem to improve the models. Regression analysis in the long-run are therefore conducted using normal standard errors.

In Table 8, all of the regressions that are conducted using the MSCI World as the benchmark return when calculating the CARs are displayed, both with and without the region dummy. This includes the value- and equal weighted index for both a 12- and 36-month time frame. The complete regressions can all be found in Appendix E. The most important finding of the regression analyses is that the coefficients of *DFINTECH* are all above 0, indicating that a firm being classified as fintech has a positive effect on the long-run stock performance. When using the equal-weighted index as a benchmark over a 3-year time period, the coefficient is significant at the 10% level and shows that the cumulative abnormal returns of fintech firms are 11.6% higher than that of non-fintech firms in the three years after the IPO. These findings go against hypothesis *H2*, as it was expected that these coefficients were negative. However, Gandolfi (2018) mentioned that despite their findings of industries not being a determinant for the performance of the stocks, the technological sector performed slightly better in the long-run than the other industries considered in their analysis. As the fintech firms could certainly be considered amongst the technological sector,[45] these results are quite corresponding with that of Gandolfi (2018). Something which is also worth mentioning is the fact that the coefficients of *DFINTECH* over the 12-month time periods are lower than that of the 36-month time periods. This is an interesting finding, as the means of the 1-year post-IPO returns were all higher than the 3-year ones when tested if they significantly differ from 0.[46] This implies that, despite these higher means for the 1-year time period, the effect of a firm being classified as fintech on the post-IPO stock returns is higher when considering a three-year time frame. The latter shows that testing if the means are statistically different from zero is only sufficient to use as a first

[44] For the analysis containing firms from both Europe and the United States the rule of thumb resulted in the following threshold for Cook's distance: 4 / (899-8-1) = 0.004494. For DFITS the treshold equals 2 * √ (8/899) = 0.18866. Adhering to these rules of thumbs resulted in excluding 43 observations from the analysis and a total sample of 839 firms.

[45] Firms are classified as fintech in the analysis when they are part of a major SIC group that belongs to the financial sector and have one of the SIC-codes that belongs to the technological industry.

[46] As described in the section before and displayed in Appendix C.

impression and that these higher means in the 1-year CAR's are most probable due to some major outliers, which are of course indicated and excluded from the analysis before running the regressions.

TABLE 9. OLS REGRESSION ON CUMULATIVE ABNORMAL RETURNS

	(1) MSCI World (VW_12)	(2) MSCI World (VW_12)	(3) MSCI World (EW_12)	(4) MSCI World (EW_12)	(5) MSCI World (VW_36)	(6) MSCI World (VW_36)	(7) MSCI World (EW_36)	(8) MSCI World (EW_36)
DFINTECH	.059	.062	.067	.07	.101	.114	.103	.116*
	(.051)	(.051)	(.051)	(.051)	(.07)	(.07)	(.07)	(.07)
AGE	.015	.016	.016	.016	.039**	.041***	.04***	.042***
	(.011)	(.011)	(.011)	(.011)	(.015)	(.015)	(.015)	(.015)
REVENUE	-.005	-.005	-.005	-.005	.009	.01	.009	.01
	(.006)	(.006)	(.006)	(.006)	(.009)	(.009)	(.009)	(.009)
DVENTCAP	.053	.044	.056	.047	.109*	.072	.108*	.071
	(.044)	(.044)	(.044)	(.044)	(.061)	(.061)	(.061)	(.061)
PROCEEDS	-.017	-.016	-.015	-.015	-.013	-.01	-.012	-.01
	(.011)	(.011)	(.011)	(.011)	(.015)	(.015)	(.015)	(.015)
DHQ_UNDRW	.051	.037	.051	.038	.134***	.079	.133***	.078
	(.036)	(.037)	(.036)	(.037)	(.05)	(.051)	(.05)	(.051)
INDEX_WORLD	-.126	-.08	-.085	-.038	-.114	.076	.016	.206
	(.491)	(.492)	(.492)	(.493)	(.683)	(.678)	(.684)	(.679)
DDELIST_36	-.017	-.012	-.012	-.008	-.005	.014	-.007	.011
	(.051)	(.051)	(.052)	(.052)	(.072)	(.071)	(.072)	(.071)
_cons								
Observations	839	839	839	839	839	839	839	839
R-squared	.058	.061	.074	.076	.09	.108	.093	.112
Year dummy	YES	YES	YES	YES	YES	YES	YES	YES
Region Dummy	NO	YES	NO	YES	NO	YES	NO	YES

Data on IPOs of financial firms between 2008-2017 from the United States and Europe. The dependent variables are the cumulative abnormal returns with the value-and equal-weighted MSCI World index returns used as benchmark, for both a 12- and 36-month time frame. Elaborations and calculations of the independent variables can be found in chapter 4.2. The data is retrieved from Thomson One, Eikon Datastream and Zephyr. Complete regressions of the analyses can be found in Appendix E: OLS regressions Standard errors are in parentheses. *** p<.01, ** p<.05, * p<.1.

As the significant positive coefficient of *DFINTECH* in model 8 is the most relevant result and this regression analysis also turns out to have the highest R-squared and therefore is the model with the highest explanatory power, the model is displayed in full in Table 9. Without any control variables included in the model, the coefficient for the variable that measures the effect of the firm being fintech or not is significant when considering a 95% confidence interval. Adding variables that control for the firm, offer and market characteristics causes this significance to vanish up until the last model, while increasing the explanatory power of the model by a considerable amount. First of all, adding a variable that controls for the age of the company at the time of the issue improves the model significantly and shows a significant positive relationship with the abnormal returns in all of the regressions. This is in line with the findings of Ritter (1991) and Brav & Gompers (1997), who state that underperformance is mostly concentrated against younger firms as the age of the company acts as an ex-ante measure of uncertainty.

TABLE 10. OLS REGRESSION ON CUMULATIVE ABNORMAL RETURNS

	(1) MSCI World (EW_36)	(2) MSCI World (EW_36)	(3) MSCI World (EW_36)	(4) MSCI World (EW_36)	(5) MSCI World (EW_36)	(6) MSCI World (EW_36)	(7) MSCI World (EW_36)	(8) MSCI World (EW_36)	(9) MSCI World (EW_36)	(10) MSCI World (EW_36)
DFINTECH	.155**	.129*	.127*	.097	.101	.087	.088	.088	.103	.116*
	(.07)	(.07)	(.07)	(.071)	(.071)	(.071)	(.071)	(.071)	(.07)	(.07)
AGE		.045***	.04***	.035**	.036**	.036**	.036**	.036**	.04***	.042***
		(.015)	(.015)	(.015)	(.015)	(.015)	(.015)	(.015)	(.015)	(.015)
REVENUE			.015**	.019**	.013	.01	.01	.01	.009	.01
			(.007)	(.007)	(.009)	(.009)	(.009)	(.009)	(.009)	(.009)
DVENTCAP				.166***	.16***	.134**	.134**	.134**	.108*	.071
				(.06)	(.06)	(.061)	(.061)	(.061)	(.061)	(.061)
PROCEEDS					.015	.001	0	0	-.012	-.01
					(.013)	(.014)	(.014)	(.015)	(.015)	(.015)
DHQ_UNDRW						.116**	.115**	.115**	.133***	.078
						(.049)	(.049)	(.049)	(.05)	(.051)
INDEX_WORLD							.258	.255	.016	.206
							(.671)	(.672)	(.684)	(.679)
DDELIST_36								-.013	-.007	.011
								(.072)	(.072)	(.071)
_cons	.061***	-.02	-.172**	-.232***	-.237***	-.175*	-.178**	-.175*		
	(.021)	(.034)	(.084)	(.086)	(.086)	(.09)	(.09)	(.092)		
Observations	839	839	839	839	839	839	839	839	839	839
R-squared	.006	.017	.021	.03	.032	.038	.038	.038	.093	.112
Year dummy	NO	NO	NO	NO	NO	NO	NO	NO	YES	YES
Region Dummy	NO	NO	NO	NO	NO	NO	NO	NO	NO	YES

Data on IPOs of financial firms between 2008-2017 from the United States and Europe. The dependent variables are the cumulative abnormal returns with the equal-weighted MSCI World index returns used as benchmark over a 36-month time frame. Elaborations and calculations of the independent variables can be found in chapter 4.2. The data is retrieved from Thomson One, Eikon Datastream and Zephyr.

Standard errors are in parentheses. *** p<.01, ** p<.05, * p<.1.

Just as in the short-term analysis, including the variable that controls for the firm being venture capital backed or not has a substantial effect on the fintech variable. When adding this variable to the analysis in model 4 of Table 10, *DFINTECH* loses its significance while *DVENTCAP* shows significant results which are maintained up to the last model. The fact that the significance disappears when adding the region dummy to the analysis shows that this positive relationship is not present when controlling for the firm being either from Europe or the United States, which implies that the effect that venture capital has on the long-run post-IPO stock performance of companies might differ between the United States and Europe,[47] something which will be addressed in the comparison between these regions hereafter.

As there were some variables that seem to have high correlation with each other, interaction terms were added to the regression in the short-term. The same is done for the long-term analyses. Interaction terms are added to the 36-month equal-and value-weighted models of which the outcome can be found in table E6 of Appendix E. Adding these interaction terms to the analyses do not change anything of noteworthy significance. They do not show any significant relationship with the cumulative abnormal returns. The coefficients for the fintech variable do also not change in terms of size and significance, while the control variables show the same characteristics as before the interaction terms are included. Furthermore, the total explanatory power of the model does not increase for both of the analyses as the R-squares remain unchanged during the additions of the interaction terms.

5.2.2. Comparing Europe and the United States

In order to compare the effects between Europe and the United States, the sample is divided into two different groups. By doing so, the difference in the magnitude and significance of the variables can be analyzed. Furthermore, the long-term stock performance of fintech companies compared to companies from the financial sector as a whole can be analyzed using different, region-based indices as benchmark return when calculating the abnormal return. However, first of all, an interaction term between the fintech variable and the region dummy is added to model 10 of Table 10. The outcome is presented in Table 11 below and shows that the cumulative abnormal returns of fintech companies in the three years after going public do not differ that

[47] This effect is also visible when looking at the 3-year post-IPO CARs calculated by using the value-weighted MSCI World index as the benchmark return in Table E5.

much between the regions when the equal-weighted MSCI World index is considered as the benchmark return. The coefficient of the interaction terms indicates that the cumulative abnormal returns of fintech companies tends to be 0.9% higher in Europe than in the United States, which is of course a neglectable percentage. Furthermore, the coefficient is not significant. As the fintech variable also loses its significance and the explanatory power of the model does not change when the interaction term is added to the analysis, no real conclusions on the hypotheses can be drawn based on these results.

TABLE 11. OLS REGRESSION ON CUMULATIVE ABNORMAL RETURNS INCLUDING INTERACTION TERM

	(1) MSCI World (EW_36)	(2) MSCI World (EW_36)
DFINTECH	.116*	.111
	(.07)	(.108)
AGE	.042***	.042***
	(.015)	(.015)
REVENUE	.01	.01
	(.009)	(.009)
DVENTCAP	.071	.071
	(.061)	(.062)
PROCEEDS	-.01	-.01
	(.015)	(.015)
DHQ_UNDRW	.078	.078
	(.051)	(.051)
INDEX_WORLD	.206	.207
	(.679)	(.68)
DDELIST_36	.011	.012
	(.071)	(.071)
1bn.REGION	-.17	-.171
	(.105)	(.106)
2.REGION	.004	.004
	(.107)	(.107)
1.DFINTECH#1bn.~N		.009
		(.14)
Observations	839	839
R-squared	.112	.112
Year dummy	YES	YES

Data on IPOs of financial firms between 2008-2017 from either the United States or Europe The dependent variables are the cumulative abnormal returns with the equal-weighted MSCI World index returns used as benchmark over a 36-month time frame. Elaborations and calculations of the independent variables can be found in chapter 4.2. The data is retrieved from Thomson One, Eikon Datastream and Zephyr. Complete regressions of the analyses can be found in Appendix E: OLS regressions

Standard errors are in parentheses. *** p<.01, ** p<.05, * p<.1.

When the firms are divided by region, the cumulative abnormal returns used as the dependent variables are calculated bases on two different indices for both of the samples. For Europe, the MSCI Europe and the STOXX 600 Europe are used to represent the market return, while for the United States the monthly returns of the NASDAQ 100 and S&P 500 are applied as the benchmark. Furthermore, both the value-and equal-weighted indices are considered. As previously mentioned, adhering to the rule-of-thumb for Cook's distance and DFITS is sufficient to improve the models significantly for the long-run analyses.[48] The outcomes of the tests for multicollinearity and heteroskedasticity, which can be found in Appendix D, show that it is not necessary to control for any of these assumptions. In Table 12, the outcome of the regression analyses on the cumulative abnormal returns over a 3-year time frame are combined in order to have a clear overview of the differences between the different indices and regions. For each different analysis, the final regression model that includes all of the control variables and the year dummy is included in the table. The complete regressions of each model can be found in Appendix E. The most relevant result that can be interpretated from this table is that the variable that measures the effect of the firm being fintech is not significant in any of the regressions considered over a three-year time frame after going public. Analyzing the complete regression models in Appendix E shows that the coefficient has not been significant in any of the models of the separate regressions, not even before adding any of the control variables. The coefficients are not only not of any statistical significance, but also positive in all of the models. When the complete regression models in Appendix E are analyzed, the relevance of adding the control variables to the long-term models becomes quite clear. Variables that control for the firm characteristics, such as *AGE* and *DVENTCAP* add a lot of explanatory power to the model. The variables that control for the market characteristics also substantially increase the R-squared of the models. However, in most of the models these variables only remain significant until adding the variable that controls for the year in which the IPO took place. This is of course something that could have been expected, as these market characteristics are dependent on the moment at which the firm went public and, thus, the year in which the IPO took place.

[48] For the analysis containing firms from Europe, the rule of thumb resulted in the following threshold for Cook's distance: 4 / (526-9-1) = 0.00775. For DFITS the threshold equals 2 * √ (9/526) = 0.18866. Adhering to these rules of thumbs resulted in excluding 36 observations from the analysis and a total sample of 490 firms. For the United States, the rule of thumb resulted in the following threshold for Cook's distance: 4 / (373-9-1) = 0.011. For DFITS the threshold equals 2 * √ (9/373) = 0.18866. Adhering to these rules of thumbs resulted in excluding 23 observations from the analysis and a total sample of 350 firms. Note that due to data availability, the regressions models containing the cumulative abnormal returns with the equal-weighted NASDAQ-100 used as the benchmark return only contains 241 firms.

TABLE 12. OLS REGRESSIONS ON CUMULATIVE ABNORMAL RETURNS (3 YEAR)

	(1) MSCI Europe (VW)	(2) MSCI Europe (EW)	(3) STOXX Europe (VW)	(4) STOXX Europe (EW)	(5) NASDAQ 100 (VW)	(6) NASDAQ 100 (EW)	(7) S&P 500 (VW)	(10) S&P 500 (EW)
DFINTECH	.109	.103	.116	.1	.045	.083	.046	.051
	(.088)	(.088)	(.088)	(.088)	(.109)	(.157)	(.109)	(.109)
AGE	.037**	.038**	.034*	.038**	.041	.01	.042	.043
	(.018)	(.018)	(.018)	(.018)	(.028)	(.04)	(.028)	(.028)
REVENUE	-.008	-.009	-.007	-.009	.038**	.069***	.036**	.036**
	(.01)	(.01)	(.01)	(.01)	(.017)	(.022)	(.017)	(.017)
DVENTCAP	-.264***	-.267***	-.262***	-.265***	.245***	.26**	.241***	.239***
	(.096)	(.096)	(.096)	(.097)	(.085)	(.109)	(.085)	(.085)
PROCEEDS	-.011	-.011	-.014	-.011	-.049	-.124**	-.051	-.051
	(.016)	(.016)	(.016)	(.016)	(.039)	(.054)	(.039)	(.039)
DHQ_UNDRW	.137**	.134**	.139**	.131**	-.019	.138	-.016	-.013
	(.065)	(.065)	(.065)	(.065)	(.089)	(.116)	(.089)	(.089)
INDEX_REGION	-.362	-.304	-.464	-.356	1.772*	4.312***	1.699*	1.785*
	(.687)	(.689)	(.686)	(.689)	(.944)	(1.481)	(.946)	(.944)
INTERESTRATE	-5.098	-4.995	-10.208	-3.82	4.684	-15.693	37.202	22.968
	(13.163)	(13.194)	(13.137)	(13.204)	(42.112)	(49.24)	(42.22)	(42.134)
DDELIST_36	-.053	-.054	-.045	-.051	.153	.171	.146	.146
	(.082)	(.082)	(.082)	(.082)	(.135)	(.166)	(.135)	(.135)
_cons								
Observations	490	490	490	490	350	241	350	350
R-squared	.162	.156	.13	.163	.172	.169	.145	.135
Year dummy	YES	YES	YES	YES	YES	YES	YES	YES

Data on IPOs of financial firms between 2008-2017 from either the United States or Europe (dependent on the index used as the benchmark return). The dependent variables are the cumulative abnormal returns with the value- and equal-weighted index returns used as benchmark over a 36-month time frame. Elaborations and calculations of the independent variables can be found in chapter 4.2. The data is retrieved from Thomson One, Eikon Datastream and Zephyr. Complete regressions of the analyses can be found in Appendix E: OLS regressions

Standard errors are in parentheses. *** p<.01, ** p<.05, * p<.1.

As mentioned before, the significance of the variable that controls for the firm being venture capital backed or not disappeared when adding the region dummy to the analysis of the entire sample, displayed in Table 10. This implied that the regions show different long-term results for venture backed companies, something which is confirmed by the findings of Table 11. While both being significant when considering a 99% confidence interval, the coefficient is negative in Europe and positive in the United States. The complete regressions included in Appendix E show that this significance is present and maintained throughout all of the models of the analyses. To put the results into perspective: firms being venture capital backed decreases the abnormal return relative to the market by around 26% in Europe, while venture backed firms outperform their non-venture-backed peers by 25% in the United States. This is of course a major difference and underlines the difference in venture capital landscapes between these regions. As previously mentioned, the venture capital market of the United States is much more developed than its European equivalent (Black & Gilson, 1998). Brav & Gompers (1997) and Loughran & Ritter (1995) both provide evidence of better performance by American firms conducting an IPO that are backed by venture capital. These results show that this is certainly also the case when considering financial firms from the US between 2008 and 2017.

When considering a 1-year post-IPO time frame, the findings are in accordance with those of the analyses considering the three years after the IPO. The outcomes of these regressions are displayed in table E15 of Appendix E. *DFINTECH* is not significant in any of the regression models and analyzing the complete regression models in Appendix E show that this has been the case throughout all the models, also before adding any of the control variables. Furthermore, the coefficients are not only not of any statistical significance, but also positive in all of the models. As hypothesis *H2* states that the underperformance was expected to be higher for the fintech companies when compared to companies of the entire financial industry as a whole, these findings are contrary to hypothesis *H2*. Supplemented with the findings of the regression models of the combined total sample, where there was also no evidence of significant underperformance of fintech companies, hypothesis *H2* is not supported. This result is underlined by the finding of a significant positive relationship between *DFINTECH* and the cumulative abnormal returns over 3 years after the IPO calculated by using the equal-weighted MSCI World index as the benchmark return.

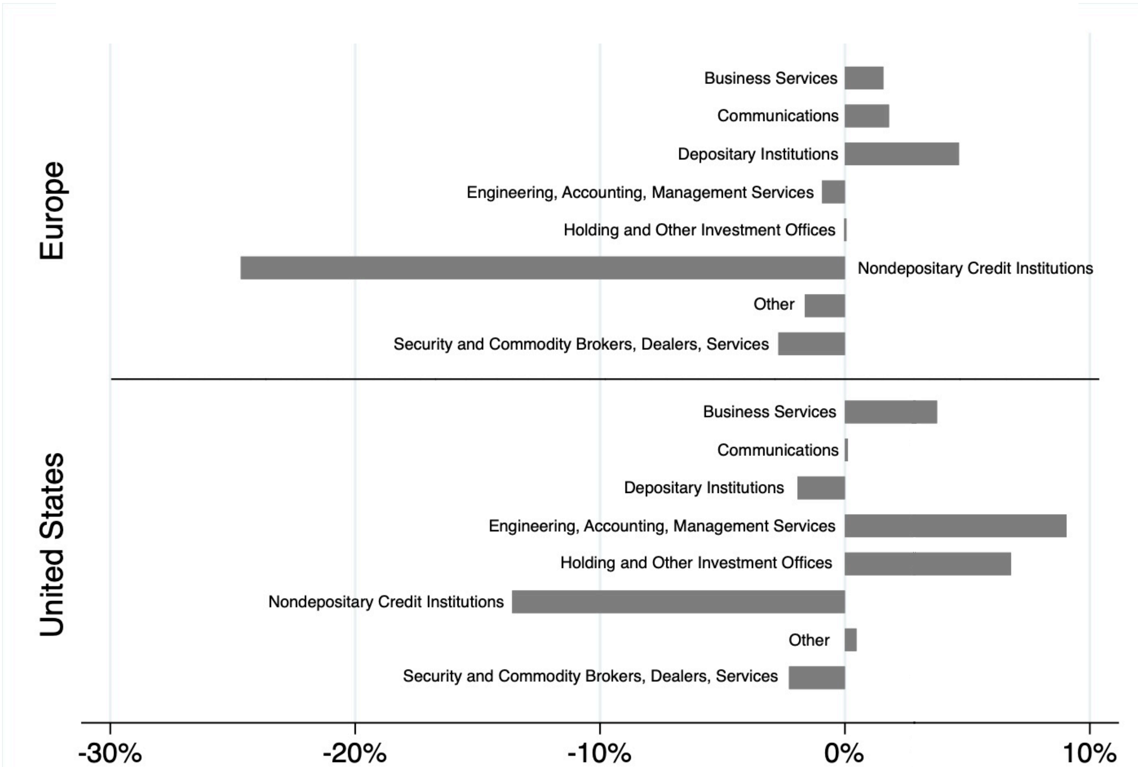
There is more evidence of fintech companies to perform better than the companies from the financial industry as a whole, rather than there is of these companies showing more severe underperformance. This could indicate that fintech is an industry that is not based on investors' sentiment driving up the stock prices of these companies, but that these firms are actually ones with high potentials and intrinsic values. Furthermore, these results are contradictory to literature suggesting that fintech could be a hype that is comparable to the dot com bubble (Cumming & Schwienbacher, 2018). As previously mentioned, Gandolfi (2018) provided evidence of the technology sector to perform better in the long-run. However, contributing these findings of fintech companies to outperform the financial industry as a whole to the technology sector would be anything but rational, as studies like the ones of Ofek & Richardson (2003) and Ljungqvist & Wilhelm (2003) provide evidence of significantly higher underperformance amongst new technology firms. Adding an interaction term between the fintech variable and the region dummy to the analysis indicates that the cumulative abnormal returns of fintech companies tend to be higher in Europe than the United States, however by a neglectable amount and not at any statistical significance. The coefficients of the fintech variable in Table 11 reveal that the positive effect of the firm being fintech has on the returns 3 year after the IPO is of greater magnitude in Europe than it is in the United States. Similar results are found when analyzing the first year after the IPO in table E15. This tendency of higher abnormal post-IPO returns in Europe is something which could have been expected, as the differences in the regulations and legal state make it easier for relatively younger firms with higher grades of uncertainty to go public in the United States. Furthermore, the European markets set more financial requirements on firms that want to go public (J. R. Ritter, 2003). As a result, the cumulative abnormal returns for fintech firms were expected to be higher in Europe, as the fintech companies that conduct an issue there can assume to be of more stable in the long-term. One can state that these findings are therefore in line with hypothesis *H2a.* However, fact that the results do not show any evidence of significant underperformance for fintech companies makes it impossible to support hypothesis H2a, which states that the underperformance by fintech companies is more severe in the United States.

As mentioned before, dividing the sample into two sub-samples containing firms from Europe and the United States also makes it able to measure the differences in stock performance between the different industries in which the fintech companies are active. Ideally, the firms should be divided into the six most relevant different segments that KPMG (2021) mentions exist for the fintech industry: Payments, Insurtech, Regtech, Wealthtech, Blockchain/Cryptocurrency and Cybersecurity. However, the absence of a SIC code for the fintech industry makes it unable to do so.[49] The fintech companies are therefore divided into different industries based on their major SIC codes. The differences in the cumulative average abnormal returns per industry over the three years after going public for Europe and the United States are displayed in Figure 4.

[49] It would have been possible to allocate the companies classified as fintech to these different sub-categories by hand. However, it would be unclear for some of the companies classified as fintech in this analysis which group they should be allocated to. This is a consequence of one of the biggest limitations of this research and will be elaborated in chapter 7: Limitations and future research.

FIGURE 4. CUMULATIVE ABNORMAL RETURNS OF FINTECH FIRMS PER INDUSTRY

Cumulative average abnormal returns (CAAR) per industry group based on the major SIC code. The CAAR's are calculated over a 36-month time frame using the value-weighted MSCI World index as the benchmark for the market return. Data on IPOs of fintech companies from the United States and Europe between 2008 and 2017, retrieved from Thomson One, Eikon Datastream and Zephyr.



While showing relatively comparable results, there are some noticeable differences between the two regions. The firms classified as fintech that are considered to be part of the depository institutions industry are performing better in Europe than the United States. This is certainly not the case for the Engineering, Accounting, Management Services and the Holding and Other Investment Offices industries. Those industries show considerably higher returns in the three years after going public in the United States. Something which also becomes clear from Figure 4 is the fact that fintech companies that belong to the non-depository credit institutions show severe underperformance relative to the MSCI World index. Furthermore, the tendency of fintech companies to perform better when compared to the market return is also visible in Figure 4, as most of the industries show positive cumulative average abnormal returns.

6. Conclusions

This research analyzed the short-and long-term post-IPO stock performance of fintech companies that went public between 2008 and 2020. The literature presents two major anomalies for initial public offerings: short-term underpricing and long-term underperformance. The goal was to test if fintech companies performed significantly different from firms of the financial sector as a whole and if there were significant differences between firms classified as fintech from Europe and the United States. In order to do so, this research tested if these anomalies presented by the literature hold for fintech companies and if these effects are more severe relative to the financial sector as a whole. Furthermore, the differences in these anomalies between Europe and the United States are analyzed to come to conclusions regarding region differences. In line with Dranev et al. (2019), firms are considered as fintech whenever they have SIC codes related to both the financial industry and the technology sector. This resulted in a total of 111 firms classified as fintech in the sample.

Using this specification for fintech companies, OLS regressions on the first-day initial returns show a significant positive relationship between the level of underpricing and firms being classified as fintech. These results prove that for the time period considered, fintech companies experience higher levels of underpricing than firms of the financial sector as a whole. This relationship remains significantly positive when variables that control for the firm, offer and market characteristics are included in the analysis. When also including variables that control for the year in which the IPO took place and the firms being either from Europe or the United States, fintech firms experience 5% more underpricing than non-fintech firms of the financial sector. These findings contribute to the studies of Karlis (2008) and Guo et al. (2005) and are in line with Salerno et al. (2021). While evidence of higher underpricing levels for internet companies is provided by Karlis (2008), Guo et al. (2005) find significantly higher initial returns for the biotech industry. The findings of this study provide evidence of the presence of an equivalent effect for IPOs in the fintech industry, confirming the findings of Salerno et al. (2021). When the differences between firms from Europe and the United States are analyzed, it becomes clear that the effect of higher underpricing levels for fintech companies tends to be of higher magnitude in the United States. However, the difference is not profound and equal to around one percentage point.

There is not any evidence found of the presence of long-term underperformance for companies from the fintech industry. Both the first and three years after the firms going public are analyzed and the cumulative abnormal returns are calculated using different value-and equal-weighted indices as the benchmark return. In fact, OLS regressions on the cumulative abnormal returns even provide significant evidence of higher returns for fintech companies in the three years after the IPO when the equal-weighted MSCI World index is used as the benchmark return. When adding all the control variables to the analysis, the fintech companies experience 11.6% higher returns than the non-fintech firms included in the sample. These findings can be considered as contrary to those of Ofek & Richardson (2003) and Ljungqvist & Wilhelm (2003), who report significantly higher underperformance levels amongst new technology firms. The fact that there is no evidence found on fintech firms underperforming the market indices strengthens claims made by Ferreira et al. (2015) and Heap and Pollari (2015) on the potential of the industry and the impact it could have on the entire finance sector. The effect of fintech firms to perform better than the non-fintech firms included in the analysis in the three years after going public tends to be stronger in Europe than in the United States. However, as no significant effect is found when dividing the samples into the two regions, no real conclusions on the differences in the magnitude of the effect can be drawn based on these results.

The outcome can be of interest to investors and fintech companies from Europe and the United States that are to conduct an initial public offering. For the issuing companies, together with the underwriters that handle the IPOs, it is particularly relevant to take the presence of higher underpricing levels in the fintech industry into account. By being aware of these results op front, they could potentially increase the offer price in order to decrease the costs to the issuer by leaving less money on the table (Loughran & Ritter, 2002). The main point of interest for the investors would be that, generally, the short-term gains of the first-day returns tend not to be offset by long-term losses and fintech firms could therefore be worth looking into when seeking for profitable long-term investments.

7. Limitations and future research

The biggest limitation of this research is the absence of a SIC code that belongs to the fintech industry. As a consequence, an alternative approach to identify fintech companies must be applied. While the method proposed by Dranev et al. (2019) is certainly sufficient to conduct the research, it does not efficiently address the industry as a whole. Some firms that are unmistakably considered as fintech, such as Adyen and Paypal, are not included in the sample due to the lack of having SIC codes that allocates them to the financial industry. On the other hand, some firms in the sample that are classified as fintech might rationally not be regarded as such. This problem could have been avoided by manually selecting the companies that are representing the fintech industry in the analysis, as is done by Salerno et al. (2021). However, the authors rightfully make the remark that this method is very prone to the selection bias. If the fintech sector would have its own code to allocate the companies to the industry, future researchers would be able to conduct more efficient research on it.

Another remark that should be made concerns the long-term stock returns. As mentioned before, long-term results should always be treated with caution as measuring performances over a longer horizon has its limitations (Lyon et al., 1999; Kothari & Warner, 1997). Furthermore, using the cumulative abnormal returns (CAR) to calculate the long-term stock returns also causes biases as it implies monthly rebalancing and does not take monthly compounding into account. Other methods of calculating the long-term stock returns could therefore be used, such as the buy-and-hold abnormal returns (BHAR), Fama-French Three-Factor Model or the Carhart Four-Factor Model. Moreover, other reference portfolios than the indices used in this research could be computed to serve as the benchmark return. One could construct reference portfolios consisting of similar firms in terms of size and book-to-market ratio. This would ensure that the returns of the fintech companies are compared to more comparable equivalents and claims on the performance of these companies would therefore be even more substantiated.

Finally, one should always be aware of the fact that the countries in Europe differ in terms of size and regulations when conducting research on that region. The indices used to control for the return of the European market in the 15 days prior to the IPO and as the benchmarks for the market return when calculating the cumulative abnormal returns for the European sample, do for instance not take the differences between the exchange markets into account. Measuring the market returns by the returns of the exchange that the IPO is issued at would therefore improve the analysis for the European sample.

This research also provides results on firms that are venture capital backed that could be of interest for future researchers. Although originally used as control variable, the coefficients are significant in almost all the regression analysis and are therefore certainly worth mentioning. In the short-term, firms that are venture capital backed show significantly higher levels of underpricing than non-venture capital backed firms, which is in line with the findings of Lee & Wahal (2004). Moreover, this effect is of greater magnitude than that of the firm being classified as fintech has on the first-day returns. Analyzing the effect that venture capital has on the long-term cumulative abnormal returns of firms shows some more interesting results. While both of the relationships are significant when considering a 99% confidence interval, European firms tend to perform worse when backed by venture capital while these firms from the United States tend to outperform its non-venture capital backed peers. As the size of these effects both lies around 25%, these are results that are certainly worth looking into by future researchers.

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9. Appendix

Appendix A: Descriptive statistics (Long-run sample)

TABLE A1. DESCRIPTIVE STATISTICS (LONG-RUN)

VARIABLES	(1) mean	(2) median	(3) min	(4) max	(5) sd	(6) N
Firm Characteristics						
Age (in years)	14.08	6	0	296	26.46	899
Europe	15.46	7	0	296	29.63	526
United States	12.14	6	0	149	21.07	373
REVENUE	11.05	11.31	0	18.18	2.792	899
Europe	10.98	11.28	1.386	18.18	3.024	526
United States	11.15	11.26	0	17.24	2.443	373
DVENTCAP	0.157				0.364	899
Europe	0.0837				0.277	526
United States	0.260				0.439	373
Offer characteristics						
PROCEEDS	4.412	4.605	-7.567	9.791	1.913	899
Europe	4.200	4.429	-7.567	8.381	2.271	526
United States	4.711	4.689	1.249	9.791	1.186	373
DHQ_UNDRW	0.423				0.494	899
Europe	0.291				0.455	526
United States	0.609				0.489	373
Market Characteristics						
INDEX*	0.00642	0.00872	-0.132	0.114	0.0297	899
Europe	0.00456	0.00363	-0.182	0.163	0.0373	526
United States	0.00970	0.0118	-0.122	0.131	0.0351	373
INTEREST						
Europe	0.00468	0.00209	-0.00332	0.0496	0.0107	526
United States	0.00311	0.00130	0.000600	0.0345	0.00448	373
Delisting variable						
DDELIST_36	0.0923				0.290	899
Europe	0.110				0.314	526
United States	0.0670				0.250	373

Data on IPOs for 2008-2017. The elaborations and calculations of the independent variables can be found in chapter 4.2. For the dummy variables, only the mean and the standard deviation are presented. The means represent what percentage of the observations have the value of 1. The data is retrieved from Thomson One, Eikon Datastream and Zephyr. *MSCI World is used for the total sample, Nasdaq composite and MSCI Europe for US and EU respectively.

Appendix B: Correlation matrix (Long-run sample)

TABLE B1. CORRELATION MATRIX: TOTAL SAMPLE (LONG-RUN)

Variables	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
(1) DFINTECH	1.000									
(2) AGE	0.113	1.000								
(3) REVENUE	0.043	0.174	1.000							
(4) DVENTCAP	0.190	0.100	-0.176	1.000						
(5) PROCEEDS	0.004	0.047	0.542	-0.024	1.000					
(6) DHQ_UNDRW	0.108	0.072	0.392	0.133	0.539	1.000				
(7) INTERESTRATE	-0.053	-0.017	-0.126	-0.043	-0.252	-0.071	1.000			
(8) INDEX_REGION	-0.024	-0.021	0.008	0.022	0.076	0.075	-0.120	1.000		
(9) INDEX_WORLD	-0.060	-0.006	0.010	-0.026	0.072	0.047	-0.143	0.901	1.000	
(10) DDELIST_36	-0.013	-0.043	-0.098	-0.032	-0.255	-0.094	0.121	-0.076	-0.045	1.000

Pearson's correlation coefficients for all the variables used in the short-term analysis. Data on IPOs between 2008-2017 for firms from both Europe and the United States, retrieved from Thompson One, Eikon and Zephyr.

Appendix C: T-tests

TABLE C1. T-TEST ON INITIAL RETURN BY CALENDAR YEAR

		IR	t-stat	№ of IPOs
2008	*Total*	.022	.695	37
	Fintech	.380	-	1
2009	*Total*	.112	2.891***	39
	Fintech	.422	1.486	4
2010	*Total*	.081	3.029***	98
	Fintech	.297	1.135	9
2011	*Total*	.068	4.66***	82
	Fintech	.165	3.47***	11
2012	*Total*	.144	5.098***	70
	Fintech	.182	3.675***	8
2013	*Total*	.082	6.588***	124
	Fintech	.093	2.614**	13
2014	*Total*	.098	4.477***	163
	Fintech	.229	2.51**	12
2015	*Total*	.09	3.81***	136
	Fintech	.064	3.999***	15
2016	*Total*	.046	3.738***	74
	Fintech	.208	2.813**	6
2017	*Total*	.065	4.641***	132
	Fintech	.104	3.367***	12
2018	*Total*	.074	2.663***	123
	Fintech	.093	1.036	5
2019	*Total*	.126	6.476***	88
	Fintech	.243	4.09***	8
2020	*Total*	.168	5.094***	121
	Fintech	.252	2.488**	11

T-test on means to be significantly different from 0. Data on IPOs between 2008-2020 for firms from the United States and Europe displayed per year for both the total sample and fintech firms only. Data retrieved from Thompson One, Eikon Datastream and Zephyr. *** *p<.01*, ** *p<.05*, * *p<.1*

TABLE C 2. T-TESTS ON INITIAL RETURN BY REGION

	Mean	t-value	St Dev	obs
Europe	**.054**	**10.873*** **	**.131**	**683**
Non-Fintech	.05	9.665***	.128	620
Fintech	.099	5.415***	.145	63
United States	**.106**	**13.772*** **	**.187**	**590**
Non-Fintech	.099	12.376***	.186	542
Fintech	.183	7.221***	.176	48
Total	**.078**	**17.323*** **	**.161**	**1273**
Non-fintech	.073	15.516***	.16	1162
Fintech	.136	8.709***	.164	111

T-test on means to be significantly different from 0. Data on IPOs between 2008-2020 for firms from the United States and Europe displayed per region for fintech and non-fintech firms. Data retrieved from Thompson One, Eikon Datastream and Zephyr.

**** p<.01, ** p<.05, * p<.1*

TABLE C 3. T-TEST ON CUMULATIVE ABNORMAL RETURNS WITH MSCI WORLD INDEX USED AS BENCHMARK RETURN

	Mean	t value	St Dev	obs
Total:				
Value-weighted (36 months)	**-.048**	**-1.822***	**.785**	**899**
Equal-weighted (36 months)	**.052**	**2.001****	**.785**	**899**
Value-weighted (12 months)	**.037**	**2.47****	**.449**	**899**
Equal-weighted (12 months)	**.068**	**4.549*****	**.45**	**899**
NonFintech				
Value-weighted (36 months)	**-.063**	**-2.288****	**.786**	**812**
Equal-weighted (36 months)	**.036**	**1.314**	**.785**	**812**
Value-weighted (12 months)	**.032**	**2.054****	**.446**	**812**
Equal-weighted (12 months)	**.062**	**3.982*****	**.447**	**812**
Fintech				
Value-weighted (36 months)	**.096**	**1.168**	**.768**	**87**
Equal-weighted (36 months)	**.204**	**2.454****	**.774**	**87**
Value-weighted (12 months)	**.083**	**1.603**	**.479**	**87**
Equal-weighted (12 months)	**.122**	**2.401****	**.476**	**87**

T-test on means to be significantly different from 0. Data on IPOs between 2008-2020 for firms from the United States and Europe displayed per region for fintech and non-fintech firms. Data retrieved from Thompson One, Eikon Datastream and Zephyr.

**** p<.01, ** p<.05, * p<.1*

TABLE C 4. T-TEST ON CUMULATIVE ABNORMAL RETURNS BY REGION (3 YEARS)

	Mean	t value	St Dev	obs
Total:				
Europe:				
MSCI Europe (VW)	.005	.158	.74	526
MSCI Europe (EW)	.005	.168	.74	526
STOXX Europe (VW)	-.056	-1.742*	.729	526
STOXX Europe (EW)	-.065	-2.023**	.74	526
United States:				
NASDAQ 100 (VW)	-.209	-4.801***	.842	373
NASDAQ 100 (EW)	-.111	-1.926	.93	260
S&P 500 (VW)	.04	.894	.848	373
S&P 500 (EW)	-.029	-.65	.849	373
NonFintech				
Europe:				
MSCI Europe (VW)	-.007	-.211	.745	482
MSCI Europe (EW)	-.007	-.219	.745	482
STOXX Europe (VW)	-.068	-2.014**	.735	482
STOXX Europe (EW)	-.077	-2.281**	.745	482
United States:				
NASDAQ 100 (VW)	-.228	-4.916***	.842	330
NASDAQ 100 (EW)	-.135	-2.23**	.929	235
S&P 500 (VW)	.025	.523	.848	330
S&P 500 (EW)	-.044	-.944	.849	330
Fintech				
Europe:				
MSCI Europe (VW)	.14	1.371	.675	44
MSCI Europe (EW)	.146	1.439	.673	44
STOXX Europe (VW)	.076	.771	.657	44
STOXX Europe (EW)	.068	.677	.668	44
United States:				
NASDAQ 100 (VW)	-.068	-.53	.843	43
NASDAQ 100 (EW)	.115	.616	.931	25
S&P 500 (VW)	.153	1.176	.854	43
S&P 500 (EW)	.09	.697	.851	43

T-test on means to be significantly different from 0. Data on IPOs between 2008-2017 for firms from the United States and Europe displayed per region for fintech and non-fintech firms. Data retrieved from Thompson One, Eikon Datastream and Zephyr.

**** p<.01, ** p<.05, * p<.1*

TABLE C 5. T-TEST ON CUMULATIVE ABNORMAL RETURNS BY REGION (1 YEAR)

	Mean	t value	St Dev	obs
Total:				
Europe:				
MSCI Europe (VW)	.073	3.647***	.463	526
MSCI Europe (EW)	.076	3.744***	.468	526
STOXX Europe (VW)	.038	1.949*	.453	526
STOXX Europe (EW)	.05	2.438**	.466	526
United States:				
NASDAQ 100 (VW)	-.038	-1.656*	.442	373
NASDAQ 100 (EW)	.022	.749	.472	260
S&P 500 (VW)	.048	2.073**	.441	373
S&P 500 (EW)	.017	.735	.44	373
NonFintech				
Europe:				
MSCI Europe (VW)	.065	3.093***	.463	482
MSCI Europe (EW)	.068	3.162***	.468	482
STOXX Europe (VW)	.03	1.469	.451	482
STOXX Europe (EW)	.041	1.917*	.466	482
United States:				
NASDAQ 100 (VW)	-.036	-1.518	.434	330
NASDAQ 100 (EW)	.022	.743	.466	235
S&P 500 (VW)	.049	2.053**	.433	330
S&P 500 (EW)	.018	.744	.433	330
Fintech				
Europe:				
MSCI Europe (VW)	.167	2.391**	.462	44
MSCI Europe (EW)	.175	2.519**	.46	44
STOXX Europe (VW)	.13	1.84*	.467	44
STOXX Europe (EW)	.146	2.11**	.46	44
United States:				
NASDAQ 100 (VW)	-.05	-.655	.498	43
NASDAQ 100 (EW)	.016	.148	.539	25
S&P 500 (VW)	.035	.453	.498	43
S&P 500 (EW)	.009	.121	.493	43

T-test on means to be significantly different from 0. Data on IPOs between 2008-2017 for firms from the United States and Europe displayed per region for fintech and non-fintech firms. Data retrieved from Thompson One, Eikon Datastream and Zephyr.

*** *p<.01*, ** *p<.05*, * *p<.1*

Appendix D: Addressing multicollinearity and heteroskedasticity

TABLE D1. VIF TEST STATISTICS (SHORT TERM)

Variable	**VIF (Total)**	**VIF (EU)**	**VIF (US)**
PROCEEDS	1.790	1.870	2.110
REVENUE	1.550	1.590	1.660
DHQ_UNDRW	1.510	1.470	1.720
DVENTCAP	1.110	1.050	1.200
AGE	1.030	1.080	1.050
DFINTECH	1.020	1.020	1.080
INDEX_WORLD	1.010		
INDEX_REGION		1.020	1.020
INTERESTRATE		1.090	1.060
Mean VIF	1.290	1.270	1.360

Variance inflation factor test statistics for the regressions on the total sample and Europe and United States separately. Data on IPOs of financial firms between 2008-2020. Data retrieved from Thomson One, Eikon Datastream and Zephyr. The VIF test measures the effect of an upward inflation on the standard errors.

TABLE D 2. VIF TEST STATISTICS (LONG-TERM)

Variable	VIF (Total)	VIF (EU)	VIF (US)
PROCEEDS	1.850	1.990	1.940
REVENUE	1.590	1.630	1.590
DHQ_UNDRW	1.520	1.580	1.540
DVENTCAP	1.140	1.080	1.140
AGE	1.060	1.140	1.060
DFINTECH	1.060	1.040	1.060
INDEX_WORLD	1.010		
INDEX_REGION		1.030	1.030
INTERESTRATE		1.120	1.100
DDELIST_36	1.080	1.110	1.080
Mean VIF	1.290	1.300	1.280

Variance inflation factor test statistics for the regressions on the total sample and Europe and United States separately. Data on IPOs of financial firms between 2008-2017. Data retrieved from Thomson One, Eikon Datastream and Zephyr. The VIF test measures the effect of an upward inflation on the standard errors.

ADDRESSING HETEROSKEDASTICITY: SHORT-TERM ANALYSIS

TABLE D 3. BREUSCH-PAGAN TEST (SHORT-TERM)

Breusch-Pagan / Cook-Weisberg test for heteroskedasticity
Ho: Constant variance
Variables: fitted values of IR
chi2(1) = 128.73
Prob > chi2 = 0.0000

TABLE D 4. WHITE-GENERAL TEST

White's test for Ho: homoskedasticity
against Ha: unrestricted heteroskedasticity
chi2(32) = 113.49
Prob > chi2 = 0.0000

TABLE D 5. SQUARED-RESIDUAL ANALYSIS (SHORT TERM)

	(1)
VARIABLES	resid2
yhat	0.0606
	(0.158)
yhat2	1.081
	(0.785)
Constant	0.0112
	(0.00693)
Observations	1,273
Prob>F	**0.0000**
R-squared	0.033

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

ADDRESSING HETEROSKEDASTICITY: LONG-TERM ANALYSIS

BRAUSCH-PAGAN TESTS:

Breusch-Pagan / Cook-Weisberg test for heteroskedasticity
Ho: Constant variance
Variables: fitted values of CAR_SP_VW_36
chi2(1) = 5.20
Prob > chi2 = 0.0226

Breusch-Pagan / Cook-Weisberg test for heteroskedasticity
Ho: Constant variance
Variables: fitted values of CAR_STOXX_VW_36
chi2(1) = 3.12
Prob > chi2 = 0.0774

Breusch-Pagan / Cook-Weisberg test for heteroskedasticity
Ho: Constant variance
Variables: fitted values of CAR_MSCIWORLD_VW_36
chi2(1) = 0.67
Prob > chi2 = 0.4140

WHITE-GENERAL TESTS:

White's test for Ho: homoskedasticity
against Ha: unrestricted heteroskedasticity
chi2(50) = 58.09
Prob > chi2 = 0.2018

White's test for Ho: homoskedasticity
against Ha: unrestricted heteroskedasticity
chi2(49) = 65.79
Prob > chi2 = 0.0549

White's test for Ho: homoskedasticity
against Ha: unrestricted heteroskedasticity
chi2(50) = 58.09
Prob > chi2 = 0.2018

Squared-Residual analysis (Long-term)

World

VARIABLES	(1) resid2
yhat	0.124
	(0.183)
yhat2	-3.040**
	(1.416)
Constant	0.363***
	(0.0271)
Observations	839
Prob>F	**0.0817**
R-squared	0.006

Standard errors in parentheses

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

Europe

VARIABLES	(1) resid2
yhat	0.277
	(0.212)
yhat2	0.489
	(0.701)
Constant	0.311***
	(0.0360)
Observations	350
Prob>F	**0.1021**
R-squared	0.013

Standard errors in parentheses

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

United States

VARIABLES	(1) resid2
yhat	-0.0613
	(0.224)
yhat2	-1.702*
	(0.958)
Constant	0.266***
	(0.0212)
Observations	479
Prob>F	**0.0672**
R-squared	0.011

Standard errors in parentheses

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

Appendix E: OLS regressions

TABLE E 1. OLS REGRESSION ON INITIAL RETURNS (EU FIRMS ONLY)

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
	IR	IR	IR	IR	IR	IR	IR	(IR)	IR
DFINTECH	.049***	.049**	.049**	.049**	.048**	.049**	.049**	.046**	.042**
	(.019)	(.019)	(.019)	(.019)	(.019)	(.019)	(.019)	(0.19)	(.019)
AGE		.001	.001	.001	0	0	0	0	.001
		(.003)	(.003)	(.003)	(.003)	(.003)	(.003)	(.003)	(.004)
REVENUE			-.001	-.001	.002	.002	.002	.002)	.001
			(.002)	(.002)	(.002)	(.002)	(.002)	(.002)	(.002)
DVENTCAP				-.007	-.003	-.003	-.004	-.005	-.009
				(.024)	(.025)	(.025)	(.024)	(.024)	(.025)
PROCEEDS					-.006**	-.007**	-.007**	-.009**	-.007**
					(.003)	(.003)	(.003)	(.003)	(.003)
DHQ_UNDRW						.01	.01	.012	.01
						(.011)	(.012)	(.12)	(.012)
INDEX_REGION							.156	.132	.1
							(.137)	(.133)	(.138)
INTERESTRATE								-.972	-.844
								(676)	(3.564)
_cons	.05***	.049***	.055***	.057***	.054***	.058***	.058***	-0.67***	
	(.005)	(.007)	(.019)	(.02)	(.02)	(.021)	(.021)	(.023)	
Observations	683	683	683	683	683	683	683	683	683
R-squared	.012	.012	.012	.012	.02	.021	.023	.028	.192
Year Dummy	NO	NO	NO	NO	NO	NO	NO	NO	YES

Data on IPOs of financial firms between 2008-2020 from Europe. The dependent variables are the initial returns, calculated by taking the natural logarithm of the closing stock price after 1 trading day divided by the offer price. Elaborations and calculations of the independent variables can be found in chapter 4.2.The data is retrieved from Thomson One, Eikon Datastream and Zephyr.

Standard errors are in parentheses. *** p<.01, ** p<.05, * p<.1.

TABLE E 2. OLS REGRESSION ON INITIAL RETURNS (US FIRMS ONLY)

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
	IR	IR	IR	IR	IR	IR	IR	IR	IR
DFINTECH	.084***	.081***	.074***	.048*	.04	.043	.045*	.041	.053*
	(.026)	(.027)	(.027)	(.028)	(.027)	(.027)	(.027)	(.028)	(.027)
AGE		.014***	.014***	.011**	.015***	.014***	.015***	.015***	.016***
		(.005)	(.005)	(.005)	(.005)	(.005)	(.005)	(.005)	(.005)
REVENUE			.006**	.01***	.002	.003	.003	.003	.002
			(.003)	(.003)	(.004)	(.004)	(.004)	(.004)	(.004)
DVENTCAP				.093***	.088***	.092***	.09***	.094***	.086***
				(.02)	(.019)	(.02)	(.019)	(.02)	(.02)
PROCEEDS					.026***	.03***	.029***	.028***	.028***
					(.007)	(.008)	(.008)	(.008)	(.008)
DHQ_UNDRW						-.018	-.018	-.018	-.021
						(.018)	(.018)	(.018)	(.02)
INDEX_REGION							.43**	.424**	.286
							(.206)	(.207)	(.217)
INTERESTRATE								-1.049	-1.037
								(.98)	(4.028)
_cons	.099***	.072***	.003	-.062*	-.103***	-.114***	-.117***	-.113***	
	(.008)	(.012)	(.036)	(.037)	(.039)	(.041)	(.041)	(.041)	
Observations	590	590	590	590	590	590	590	590	590
R-squared	.015	.023	.029	.079	.098	.1	.107	.109	.351
Year Dummy	NO	NO	NO	NO	NO	NO	NO	NO	YES

Data on IPOs of financial firms between 2008-2020 from the United States. The dependent variables are the initial returns, calculated by taking the natural logarithm of the closing stock price after 1 trading day divided by the offer price. Elaborations and calculations of the independent variables can be found in chapter 4.2.The data is retrieved from Thomson One, Eikon Datastream and Zephyr.

Standard errors are in parentheses. *** p<.01, ** p<.05, * p<.1.

TABLE E 3. OLS REGRESSION ON CUMULATIVE ABNORMAL RETURNS

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
	CAR_MS CIWORL D_VW_12	CAR_MS CIWORL D_VW_12	CAR_MS CIWORL D_VW_12	CAR_MS CIWORL D_VW_12	CAR_MS CIWORL D_VW_12	CAR_MS CIWORL D_VW_12	CAR_MS CIWORL D_VW_12	CAR_MS CIWORL D_VW_12	CAR_MS CIWORL D_VW_12	CAR_MS CIWORL D_VW_12
DFINTECH	.069	.061	.062	.05	.048	.044	.042	.043	.059	.062
	(.05)	(.05)	(.05)	(.051)	(.051)	(.051)	(.051)	(.051)	(.051)	(.051)
AGE		.014	.017	.015	.015	.015	.015	.015	.015	.016
		(.011)	(.011)	(.011)	(.011)	(.011)	(.011)	(.011)	(.011)	(.011)
REVENUE			-.008	-.006	-.003	-.004	-.004	-.004	-.005	-.005
			(.005)	(.005)	(.006)	(.007)	(.007)	(.007)	(.006)	(.006)
DVENTCAP				.07	.073*	.065	.065	.064	.053	.044
				(.043)	(.043)	(.044)	(.044)	(.044)	(.044)	(.044)
PROCEEDS					-.008	-.012	-.012	-.013	-.017	-.016
					(.009)	(.01)	(.01)	(.01)	(.011)	(.011)
DHQ_UNDRW						.034	.035	.036	.051	.037
						(.035)	(.035)	(.035)	(.036)	(.037)
INDEX_WORLD							-.392	-.396	-.126	-.08
							(.48)	(.481)	(.491)	(.492)
DDELIST_36								-.015	-.017	-.012
								(.052)	(.051)	(.051)
_cons	.037**	.011	.093	.068	.07	.088	.093	.096		
	(.015)	(.024)	(.059)	(.061)	(.062)	(.064)	(.065)	(.066)		
Observations	839	839	839	839	839	839	839	839	839	839
R-squared	.002	.004	.007	.01	.011	.012	.013	.013	.058	.061
Year dummy	NO	NO	NO	NO	NO	NO	NO	NO	YES	YES
Region Dummy	NO	NO	NO	NO	NO	NO	NO	NO	NO	YES

Data on IPOs of financial firms between 2008-2017 from the United States and Europe. The dependent variables are the cumulative abnormal returns with the value-weighted MSCI World index returns used as benchmark over a 12-month time frame. Elaborations and calculations of the independent variables can be found in chapter 4.2. The data is retrieved from Thomson One, Eikon Datastream and Zephyr.

Standard errors are in parentheses. *** p<.01, ** p<.05, * p<.1.

TABLE E 4. OLS REGRESSION ON CUMULATIVE ABNORMAL RETURNS

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
	CAR_MSCIWORLD_EW_12	CAR_MSCIWORLD_EW_12	CAR_MSCIWORLD_EW_12	CAR_MSCIWORLD_EW_12	CAR_MSCIWORLD_EW_12	CAR_MSCIWORLD_EW_12	CAR_MSCIWORLD_EW_12	CAR_MSCIWORLD_EW_12	CAR_MSCIWORLD_EW_12	CAR_MSCIWORLD_EW_12
DFINTECH	.081	.073	.074	.06	.059	.055	.054	.054	.067	.07
	(.05)	(.05)	(.05)	(.051)	(.051)	(.051)	(.051)	(.051)	(.051)	(.051)
AGE		.015	.018	.016	.015	.015	.015	.015	.016	.016
		(.011)	(.011)	(.011)	(.011)	(.011)	(.011)	(.011)	(.011)	(.011)
REVENUE			-.007	-.005	-.003	-.004	-.004	-.004	-.005	-.005
			(.005)	(.005)	(.006)	(.007)	(.007)	(.007)	(.006)	(.006)
DVENTCAP				.077*	.079*	.072*	.072	.071	.056	.047
				(.043)	(.043)	(.044)	(.044)	(.044)	(.044)	(.044)
PROCEEDS					-.005	-.009	-.009	-.009	-.015	-.015
					(.009)	(.01)	(.01)	(.01)	(.011)	(.011)
DHQ_UNDRW						.031	.032	.033	.051	.038
						(.035)	(.035)	(.035)	(.036)	(.037)
INDEX_WORLD							-.328	-.332	-.085	-.038
							(.48)	(.481)	(.492)	(.493)
DDELIST_36								-.016	-.012	-.008
								(.052)	(.052)	(.052)
_cons	.067***	.04	.109*	.081	.083	.099	.102	.106		
	(.015)	(.024)	(.059)	(.061)	(.061)	(.064)	(.065)	(.066)		
Observations	839	839	839	839	839	839	839	839	839	839
R-squared	.003	.006	.008	.011	.012	.013	.013	.013	.074	.076
Year dummy	NO	NO	NO	NO	NO	NO	NO	NO	YES	YES
Region Dummy	NO	NO	NO	NO	NO	NO	NO	NO	NO	YES

Data on IPOs of financial firms between 2008-2017 from the United States and Europe. The dependent variables are the cumulative abnormal returns with the equal-weighted MSCI World index returns used as benchmark over a 12-month time frame. Elaborations and calculations of the independent variables can be found in chapter 4.2. The data is retrieved from Thomson One, Eikon Datastream and Zephyr.

Standard errors are in parentheses. *** p<.01, ** p<.05, * p<.1.

TABLE E 5. OLS REGRESSION ON CUMULATIVE ABNORMAL RETURNS

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
	CAR_MSCIWORLD_VW_36	CAR_MSCIWORLD_VW_36	CAR_MSCIWORLD_VW_36	CAR_MSCIWORLD_VW_36	CAR_MSCIWORLD_VW_36	CAR_MSCIWORLD_VW_36	CAR_MSCIWORLD_VW_36	CAR_MSCIWORLD_VW_36	CAR_MSCIWORLD_VW_36	CAR_MSCIWORLD_VW_36
DFINTECH	.145**	.12*	.117*	.087	.09	.077	.077	.077	.101	.114
	(.071)	(.071)	(.071)	(.071)	(.071)	(.071)	(.072)	(.072)	(.07)	(.07)
AGE		.045***	.04***	.035**	.036**	.036**	.036**	.036**	.039**	.041***
		(.015)	(.015)	(.015)	(.015)	(.015)	(.015)	(.015)	(.015)	(.015)
REVENUE			.014*	.019**	.014	.01	.01	.01	.009	.01
			(.007)	(.008)	(.009)	(.009)	(.009)	(.009)	(.009)	(.009)
DVENTCAP				.169***	.164***	.14**	.139**	.139**	.109*	.072
				(.06)	(.061)	(.062)	(.062)	(.062)	(.061)	(.061)
PROCEEDS					.013	-.001	0	-.001	-.013	-.01
					(.013)	(.014)	(.014)	(.015)	(.015)	(.015)
DHQ_UNDRW						.106**	.106**	.107**	.134***	.079
						(.05)	(.05)	(.05)	(.05)	(.051)
INDEX_WORLD							-.186	-.187	-.114	.076
							(.675)	(.676)	(.683)	(.678)
DDELIST_36								-.001	-.005	.014
								(.073)	(.072)	(.071)
_cons	-.037*	-.119***	-.265***	-.326***	-.33***	-.273***	-.271***	-.271***		
	(.021)	(.034)	(.084)	(.087)	(.087)	(.09)	(.091)	(.092)		
Observations	839	839	839	839	839	839	839	839	839	839
R-squared	.005	.016	.02	.029	.03	.036	.036	.036	.09	.108
Year dummy	NO	NO	NO	NO	NO	NO	NO	NO	YES	YES
Region Dummy	NO	NO	NO	NO	NO	NO	NO	NO	NO	YES

Data on IPOs of financial firms between 2008-2017 from the United States and Europe. The dependent variables are the cumulative abnormal returns with the value-weighted MSCI World index returns used as benchmark over a 36-month time frame. Elaborations and calculations of the independent variables can be found in chapter 4.2. The data is retrieved from Thomson One, Eikon Datastream and Zephyr.

Standard errors are in parentheses. *** p<.01, ** p<.05, * p<.1.

TABLE E 6. OLS REGRESSION ON CUMULATIVE ABNORMAL RETURNS INCLUDING INTERACTION TERMS

	(1) MSCI World (VW_36)	(2) MSCI World (VW_36)	(3) MSCI World (VW_36)	(4) MSCI World (VW_36)	(5) MSCI World (VW_36)	(6) MSCI World (EW_36)	(7) MSCI World (EW_36)	(8) MSCI World (EW_36)	(9) MSCI World (EW_36)	(10) MSCI World (EW_36)
DFINTECH	.114	.114	.102	.114	.114	.116*	.117*	.104	.116*	.117*
	(.07)	(.07)	(.07)	(.07)	(.07)	(.07)	(.07)	(.07)	(.07)	(.07)
AGE	.041***	.041***	.041***	.041***	.041***	.042***	.042***	.042***	.042***	.042***
	(.015)	(.015)	(.015)	(.015)	(.015)	(.015)	(.015)	(.015)	(.015)	(.015)
REVENUE	.01	.01	.01	.008	.006	.01	.008	.01	.008	.004
	(.009)	(.02)	(.009)	(.011)	(.022)	(.009)	(.02)	(.009)	(.011)	(.022)
DVENTCAP	.072	.072	.093	.072	.068	.071	.071	.092	.072	.067
	(.061)	(.061)	(.062)	(.061)	(.062)	(.061)	(.061)	(.062)	(.061)	(.062)
PROCEEDS	-.01	-.01	-.006	-.01	-.01	-.01	-.012	-.005	-.01	-.013
	(.015)	(.039)	(.016)	(.015)	(.045)	(.015)	(.039)	(.016)	(.015)	(.045)
DHQ_UNDRW	.079	.079	.369*	.045	.102	.078	.078	.372**	.041	.117
	(.051)	(.052)	(.189)	(.194)	(.271)	(.051)	(.052)	(.19)	(.194)	(.272)
INDEX_WORLD	.076	.076	-.098	.087	.097	.206	.204	.032	.218	.224
	(.678)	(.679)	(.683)	(.682)	(.685)	(.679)	(.68)	(.684)	(.682)	(.686)
DDELIST_36	.014	.014	.001	.014	.015	.011	.011	-.001	.011	.013
	(.071)	(.071)	(.072)	(.071)	(.071)	(.071)	(.071)	(.072)	(.071)	(.071)
PRO#REV		0			0		0			.001
		(.004)			(.005)		(.004)			(.005)
HQU#PRO			-.044		-.017			-.045		-.021
			(.034)		(.043)			(.035)		(.044)
HQU#REV				.003	.006				.003	.006
				(.016)	(.019)				(.016)	(.019)
Observations	839	839	839	839	839	839	839	839	839	839
R-squared	.108	.108	.091	.108	.108	.112	.112	.095	.112	.112
Year dummy	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES
Region dummy	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES

Data on IPOs of financial firms between 2008-2017 from the United States and Europe. The dependent variables are the cumulative abnormal returns with the value-and equal-weighted MSCI World index returns used as benchmark, for a 36-month time frame. Elaborations and calculations of the independent variables can be found in chapter 4.2. The data is retrieved from Thomson One, Eikon Datastream and Zephyr. Complete regressions of the analyses can be found in Appendix E: OLS regressions
Standard errors are in parentheses. *** p<.01, ** p<.05, * p<.1.

TABLE E 7. OLS REGRESSION ON CUMULATIVE ABNORMAL RETURNS

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
	CAR_MSCIEU_VW_36	CAR_MSCIEU_VW_36	CAR_MSCIEU_VW_36	CAR_MSCIEU_VW_36	CAR_MSCIEU_VW_36	CAR_MSCIEU_VW_36	CAR_MSCIEU_VW_36	CAR_MSCIEU_VW_36	CAR_MSCIEU_VW_36	CAR_MSCIEU_VW_36
DFINTECH	.116	.086	.093	.107	.119	.118	.115	.094	.094	.109
	(.091)	(.092)	(.092)	(.092)	(.092)	(.091)	(.091)	(.091)	(.091)	(.088)
AGE		.041**	.034*	.037**	.039**	.035*	.035*	.035*	.034*	.037**
		(.018)	(.019)	(.019)	(.019)	(.019)	(.019)	(.019)	(.019)	(.018)
REVENUE			.013	.009	-.002	-.004	-.005	-.006	-.006	-.008
			(.009)	(.009)	(.011)	(.011)	(.011)	(.011)	(.011)	(.01)
DVENTCAP				-.198**	-.211**	-.204**	-.202**	-.219**	-.226**	-.264***
				(.1)	(.1)	(.1)	(.1)	(.1)	(.1)	(.096)
PROCEEDS					.026*	.016	.017	.006	.004	-.011
					(.014)	(.015)	(.015)	(.015)	(.016)	(.016)
DHQ_UNDRW						.103	.103	.12*	.123*	.137**
						(.067)	(.067)	(.067)	(.067)	(.065)
INDEX_REGION							-.768	-1.011	-1.051	-.362
							(.699)	(.7)	(.703)	(.687)
INTERESTRATE								-6.86***	-6.8***	-5.098
								(2.498)	(2.501)	(13.163)
DDELIST_36									-.06	-.053
									(.085)	(.082)
_cons	.014	-.058	-.192*	-.143	-.137	-.089	-.081	.005	.022	
	(.026)	(.041)	(.098)	(.101)	(.1)	(.105)	(.105)	(.109)	(.112)	
Observations	490	490	490	490	490	490	490	490	490	490
R-squared	.003	.014	.018	.026	.033	.038	.04	.055	.056	.162
Year dummy	NO	NO	NO	NO	NO	NO	NO	NO	NO	YES

Data on IPOs of financial firms between 2008-2017 from Europe. The dependent variables are the cumulative abnormal returns with the value-weighted MSCI Europe index returns used as benchmark over a 36-month time frame. Elaborations and calculations of the independent variables can be found in chapter 4.2. The data is retrieved from Thomson One, Eikon Datastream and Zephyr.

Standard errors are in parentheses. *** p<.01, ** p<.05, * p<.1.

TABLE E 8. OLS REGRESSION ON CUMULATIVE ABNORMAL RETURNS

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
	CAR_MS CIEU_E W_36	CAR_MS CIEU_EW _36	CAR_MS CIEU_EW _36	CAR_MS CIEU_EW _36	CAR_MS CIEU_EW _36	CAR_MS CIEU_EW _36	CAR_MS CIEU_EW _36	CAR_MS CIEU_EW _36	CAR_MS CIEU_EW _36	CAR_MS CIEU_EW _36
DFINTECH	.122	.091	.099	.113	.126	.125	.123	.096	.096	.103
	(.091)	(.091)	(.091)	(.091)	(.091)	(.091)	(.091)	(.091)	(.091)	(.088)
AGE		.041**	.033*	.037**	.039**	.035*	.035*	.035*	.034*	.038**
		(.018)	(.018)	(.019)	(.018)	(.019)	(.019)	(.018)	(.019)	(.018)
REVENUE			.014	.01	-.002	-.005	-.005	-.006	-.006	-.009
			(.009)	(.009)	(.011)	(.011)	(.011)	(.011)	(.011)	(.01)
DVENTCAP				-.199**	-.213**	-.207**	-.205**	-.227**	-.233**	-.267***
				(.1)	(.1)	(.1)	(.1)	(.099)	(.099)	(.096)
PROCEEDS					.029**	.02	.02	.007	.005	-.011
					(.014)	(.015)	(.015)	(.015)	(.016)	(.016)
DHQ_UNDRW						.096	.097	.118*	.12*	.134**
						(.067)	(.067)	(.067)	(.067)	(.065)
INDEX_REGION							-.53	-.841	-.878	-.304
							(.698)	(.695)	(.698)	(.689)
INTERESTRATE								-8.809***	-8.754***	-4.995
								(2.481)	(2.484)	(13.194)
DDELIST_36									-.055	-.054
									(.085)	(.082)
_cons	.015	-.058	-.198**	-.149	-.143	-.098	-.092	.018	.033	
	(.026)	(.041)	(.098)	(.1)	(.1)	(.105)	(.105)	(.108)	(.111)	
Observations	490	490	490	490	490	490	490	490	490	490
R-squared	.004	.014	.019	.027	.036	.04	.041	.066	.067	.156
Year dummy	NO	NO	NO	NO	NO	NO	NO	NO	NO	YES

Data on IPOs of financial firms between 2008-2017 from Europe. The dependent variables are the cumulative abnormal returns with the equal-weighted MSCI Europe index returns used as benchmark over a 36-month time frame. Elaborations and calculations of the independent variables can be found in chapter 4.2. The data is retrieved from Thomson One, Eikon Datastream and Zephyr.

Standard errors are in parentheses. *** p<.01, ** p<.05, * p<.1.

TABLE E9. OLS REGRESSION ON CUMULATIVE ABNORMAL RETURNS

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
	CAR_STOXX_VW_36	CAR_STOXX_VW_36	CAR_STOXX_VW_36	CAR_STOXX_VW_36	CAR_STOXX_VW_36	CAR_STOXX_VW_36	CAR_STOXX_VW_36	CAR_STOXX_VW_36	CAR_STOXX_VW_36	CAR_STOXX_VW_36
DFINTECH	.122	.089	.096	.11	.118	.118	.114	.092	.092	.116
	(.089)	(.09)	(.09)	(.09)	(.09)	(.09)	(.09)	(.089)	(.089)	(.088)
AGE		.043**	.037**	.041**	.042**	.038**	.038**	.038**	.037**	.034*
		(.017)	(.018)	(.018)	(.018)	(.018)	(.018)	(.018)	(.018)	(.018)
REVENUE			.011	.007	0	-.003	-.004	-.005	-.005	-.007
			(.009)	(.009)	(.01)	(.011)	(.011)	(.01)	(.01)	(.01)
DVENTCAP				-.205**	-.214**	-.207**	-.205**	-.224**	-.231**	-.262***
				(.098)	(.098)	(.098)	(.098)	(.097)	(.098)	(.096)
PROCEEDS					.018	.008	.008	-.003	-.006	-.014
					(.013)	(.015)	(.015)	(.015)	(.016)	(.016)
DHQ_UNDRW						.104	.105	.123*	.126*	.139**
						(.066)	(.066)	(.066)	(.066)	(.065)
INDEX_REGION							-.813	-1.074	-1.12	-.464
							(.684)	(.684)	(.687)	(.686)
INTERESTRATE								-7.354***	-7.285***	-10.208
								(2.442)	(2.444)	(13.137)
DDELIST_36									-.068	-.045
									(.083)	(.082)
_cons	-.047*	-.123***	-.236**	-.186*	-.182*	-.133	-.124	-.033	-.013	
	(.025)	(.04)	(.096)	(.098)	(.098)	(.103)	(.103)	(.107)	(.109)	
Observations	490	490	490	490	490	490	490	490	490	490
R-squared	.004	.016	.019	.028	.032	.037	.04	.057	.059	.13
Year dummy	NO	NO	NO	NO	NO	NO	NO	NO	NO	YES

Data on IPOs of financial firms between 2008-2017 from Europe. The dependent variables are the cumulative abnormal returns with the value-weighted STOXX-600 Europe index returns used as benchmark over a 36-month time frame. Elaborations and calculations of the independent variables can be found in chapter 4.2. The data is retrieved from Thomson One, Eikon Datastream and Zephyr.

Standard errors are in parentheses. *** p<.01, ** p<.05, * p<.1.

TABLE E 10. OLS REGRESSION ON CUMULATIVE ABNORMAL RETURNS

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
	CAR_STOXX_EW_36	CAR_STOXX_EW_36	CAR_STOXX_EW_36	CAR_STOXX_EW_36	CAR_STOXX_EW_36	CAR_STOXX_EW_36	CAR_STOXX_EW_36	CAR_STOXX_EW_36	CAR_STOXX_EW_36	CAR_STOXX_EW_36
DFINTECH	.112	.081	.088	.102	.115	.114	.112	.085	.085	.1
	(.091)	(.092)	(.092)	(.092)	(.092)	(.092)	(.092)	(.091)	(.091)	(.088)
AGE		.042**	.035*	.039**	.04**	.037*	.037*	.037**	.036*	.038**
		(.018)	(.019)	(.019)	(.019)	(.019)	(.019)	(.018)	(.019)	(.018)
REVENUE			.013	.009	-.003	-.005	-.006	-.007	-.007	-.009
			(.009)	(.009)	(.011)	(.011)	(.011)	(.011)	(.011)	(.01)
DVENTCAP				-.198**	-.212**	-.206**	-.204**	-.226**	-.232**	-.265***
				(.1)	(.1)	(.1)	(.1)	(.099)	(.1)	(.097)
PROCEEDS					.028**	.019	.02	.007	.004	-.011
					(.014)	(.015)	(.015)	(.015)	(.016)	(.016)
DHQ_UNDRW						.094	.095	.116*	.119*	.131**
						(.067)	(.067)	(.067)	(.067)	(.065)
INDEX_REGION							-.656	-.966	-1.005	-.356
							(.7)	(.697)	(.7)	(.689)
INTERESTRATE								-8.76***	-8.701***	-3.82
								(2.489)	(2.491)	(13.204)
DDELIST_36									-.058	-.051
									(.085)	(.082)
_cons	-.055**	-.131***	-.262***	-.213**	-.207**	-.163	-.156	-.047	-.03	
	(.026)	(.041)	(.098)	(.101)	(.1)	(.105)	(.105)	(.109)	(.112)	
Observations	490	490	490	490	490	490	490	490	490	490
R-squared	.003	.014	.019	.027	.035	.039	.041	.065	.066	.163
Year dummy	NO	NO	NO	NO	NO	NO	NO	NO	NO	YES

Data on IPOs of financial firms between 2008-2017 from Europe. The dependent variables are the cumulative abnormal returns with the equal-weighted STOXX-600 Europe index returns used as benchmark over a 36-month time frame. Elaborations and calculations of the independent variables can be found in chapter 4.2. The data is retrieved from Thomson One, Eikon Datastream and Zephyr.

Standard errors are in parentheses. *** p<.01, ** p<.05, * p<.1.

TABLE E 11. OLS REGRESSION ON CUMULATIVE ABNORMAL RETURNS

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
	CAR_NS DQ100_ VW_36	CAR_NS DQ100_V W_36	CAR_NS DQ100_V W_36	CAR_NS DQ100_V W_36	CAR_NS DQ100_V W_36	CAR_NS DQ100_V W_36	CAR_NS DQ100_V W_36	CAR_NS DQ100_V W_36	CAR_NS DQ100_V W_36	CAR_NS DQ100_V W_36
DFINTECH	.153	.133	.121	.028	.033	.041	.052	.048	.047	.045
	(.104)	(.104)	(.104)	(.108)	(.108)	(.109)	(.109)	(.109)	(.109)	(.109)
AGE		.059**	.057**	.045*	.039	.037	.038	.038	.036	.041
		(.027)	(.027)	(.027)	(.027)	(.027)	(.027)	(.027)	(.027)	(.028)
REVENUE			.013	.024*	.037**	.038**	.039**	.039**	.039**	.038**
			(.014)	(.014)	(.017)	(.017)	(.017)	(.017)	(.017)	(.017)
DVENTCAP				.244***	.249***	.264***	.261***	.258***	.258***	.245***
				(.082)	(.081)	(.085)	(.085)	(.085)	(.085)	(.085)
PROCEEDS					-.049	-.038	-.04	-.04	-.037	-.049
					(.033)	(.039)	(.039)	(.039)	(.039)	(.039)
DHQ_UNDRW						-.05	-.061	-.055	-.061	-.019
						(.087)	(.087)	(.087)	(.088)	(.089)
INDEX_REGION							1.526*	1.549*	1.499	1.772*
							(.919)	(.92)	(.921)	(.944)
INTERESTRATE								-6.934	-6.648	4.684
								(8.158)	(8.161)	(42.112)
DDELIST_36									.146	.153
									(.135)	(.135)
_cons	-.183***	-.289***	-.436***	-.575***	-.486***	-.519***	-.536***	-.513***	-.529***	
	(.034)	(.059)	(.161)	(.166)	(.176)	(.185)	(.184)	(.186)	(.187)	
Observations	350	350	350	350	350	350	350	350	350	350
R-squared	.006	.02	.022	.047	.053	.054	.062	.064	.067	.172
Year dummy	NO	NO	NO	NO	NO	NO	NO	NO	NO	YES

Data on IPOs of financial firms between 2008-2017 from the United States. The dependent variables are the cumulative abnormal returns with the value-weighted NASDAQ-100 index returns used as benchmark over a 36-month time frame. Elaborations and calculations of the independent variables can be found in chapter 4.2. The data is retrieved from Thomson One, Eikon Datastream and Zephyr.

Standard errors are in parentheses. *** p<.01, ** p<.05, * p<.1.

TABLE E 12. OLS REGRESSION ON CUMULATIVE ABNORMAL RETURNS

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
	CAR_NS DQ100_E W_36	CAR_NS DQ100_E W_36	CAR_NS DQ100_E W_36	CAR_NS DQ100_E W_36	CAR_NS DQ100_E W_36	CAR_NS DQ100_E W_36	CAR_NS DQ100_E W_36	CAR_NS DQ100_E W_36	CAR_NS DQ100_E W_36	CAR_NS DQ100_E W_36
DFINTECH	.24	.239	.205	.126	.139	.126	.138	.107	.097	.083
	(.157)	(.157)	(.158)	(.159)	(.158)	(.16)	(.158)	(.158)	(.158)	(.157)
AGE		.061	.053	.027	.021	.022	.026	.031	.028	.01
		(.04)	(.04)	(.041)	(.04)	(.041)	(.04)	(.04)	(.04)	(.04)
REVENUE			.031*	.044**	.067***	.067***	.07***	.071***	.07***	.069***
			(.018)	(.019)	(.022)	(.022)	(.022)	(.022)	(.022)	(.022)
DVENTCAP				.278**	.291***	.273**	.271**	.26**	.261**	.26**
				(.108)	(.107)	(.112)	(.11)	(.109)	(.11)	(.109)
PROCEEDS					-.08*	-.098*	-.114**	-.132**	-.126**	-.124**
					(.044)	(.054)	(.053)	(.053)	(.054)	(.054)
DHQ_UNDRW						.071	.075	.125	.117	.138
						(.115)	(.114)	(.115)	(.116)	(.116)
INDEX_REGION							3.567**	3.872***	3.818***	4.312***
							(1.413)	(1.408)	(1.411)	(1.481)
INTERESTRATE								-25.158**	-24.643**	-15.693
								(11.412)	(11.44)	(49.24)
DDELIST_36									.131	.171
									(.166)	(.166)
_cons	-.099**	-.207**	-.533**	-.699***	-.564**	-.518**	-.521**	-.406*	-.423*	
	(.045)	(.084)	(.211)	(.219)	(.23)	(.242)	(.24)	(.243)	(.244)	
Observations	241	241	241	241	241	241	241	241	241	241
R-squared	.01	.019	.031	.057	.07	.072	.097	.115	.117	.169
Year dummy	NO	NO	NO	NO	NO	NO	NO	NO	NO	YES

Data on IPOs of financial firms between 2008-2017 from the United States. The dependent variables are the cumulative abnormal returns with the equal-weighted NASDAQ-100 index returns used as benchmark over a 36-month time frame. Elaborations and calculations of the independent variables can be found in chapter 4.2. The data is retrieved from Thomson One, Eikon Datastream and Zephyr.

Standard errors are in parentheses. *** p<.01, ** p<.05, * p<.1.

TABLE E13. OLS REGRESSION ON CUMULATIVE ABNORMAL RETURNS

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
	CAR_SP_ VW_36	CAR_SP_ VW_36	CAR_SP_ VW_36	CAR_SP_ VW_36	CAR_SP_ VW_36	CAR_SP_ VW_36	CAR_SP_ VW_36	CAR_SP_ VW_36	CAR_SP_ VW_36	CAR_SP_ VW_36
DFINTECH	.112	.092	.084	-.013	-.008	-.005	.007	.017	.016	.046
	(.106)	(.106)	(.106)	(.11)	(.109)	(.111)	(.11)	(.11)	(.11)	(.109)
AGE		.059**	.058**	.044	.039	.038	.039	.038	.037	.042
		(.027)	(.027)	(.027)	(.028)	(.028)	(.028)	(.028)	(.028)	(.028)
REVENUE			.01	.021	.035**	.035**	.037**	.037**	.037**	.036**
			(.014)	(.014)	(.017)	(.017)	(.017)	(.017)	(.017)	(.017)
DVENTCAP				.256***	.261***	.267***	.264***	.271***	.272***	.241***
				(.083)	(.083)	(.087)	(.086)	(.086)	(.086)	(.085)
PROCEEDS					-.052	-.047	-.049	-.048	-.044	-.051
					(.034)	(.039)	(.039)	(.039)	(.039)	(.039)
DHQ_UNDRW						-.02	-.032	-.047	-.054	-.016
						(.089)	(.088)	(.088)	(.089)	(.089)
INDEX_REGION							1.669*	1.611*	1.558*	1.699*
							(.934)	(.93)	(.93)	(.946)
INTERESTRATE								17.104**	17.403**	37.202
								(8.247)	(8.248)	(42.22)
DDELIST_36									.152	.146
									(.136)	(.135)
_cons	.065*	-.041	-.15	-.295*	-.202	-.215	-.234	-.289	-.305	
	(.035)	(.06)	(.164)	(.168)	(.178)	(.188)	(.187)	(.188)	(.189)	
Observations	350	350	350	350	350	350	350	350	350	350
R-squared	.003	.016	.018	.044	.051	.051	.06	.071	.075	.145
Year dummy	NO	NO	NO	NO	NO	NO	NO	NO	NO	YES

Data on IPOs of financial firms between 2008-2017 from the United States. The dependent variables are the cumulative abnormal returns with the value-weighted S&P 500 index returns used as benchmark over a 36-month time frame. Elaborations and calculations of the independent variables can be found in chapter 4.2. The data is retrieved from Thomson One, Eikon Datastream and Zephyr.

Standard errors are in parentheses. *** p<.01, ** p<.05, * p<.1.

TABLE E 14. OLS REGRESSION ON CUMULATIVE ABNORMAL RETURNS

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
	CAR_SP_EW_36	CAR_SP_EW_36	CAR_SP_EW_36	CAR_SP_EW_36	CAR_SP_EW_36	CAR_SP_EW_36	CAR_SP_EW_36	CAR_SP_EW_36	CAR_SP_EW_36	CAR_SP_EW_36
DFINTECH	.113	.092	.085	-.014	-.009	-.005	.007	.014	.012	.051
	(.106)	(.105)	(.106)	(.109)	(.109)	(.11)	(.11)	(.11)	(.11)	(.109)
AGE		.061**	.06**	.047*	.041	.04	.041	.041	.04	.043
		(.027)	(.027)	(.027)	(.028)	(.028)	(.028)	(.028)	(.028)	(.028)
REVENUE			.009	.02	.035**	.035**	.037**	.037**	.037**	.036**
			(.014)	(.014)	(.017)	(.017)	(.017)	(.017)	(.017)	(.017)
DVENTCAP				.26***	.265***	.272***	.269***	.274***	.274***	.239***
				(.083)	(.083)	(.086)	(.086)	(.086)	(.086)	(.085)
PROCEEDS					-.054	-.048	-.05	-.049	-.046	-.051
					(.034)	(.039)	(.039)	(.039)	(.039)	(.039)
DHQ_UNDRW						-.022	-.034	-.045	-.051	-.013
						(.088)	(.088)	(.088)	(.089)	(.089)
INDEX_REGION							1.697*	1.657*	1.605*	1.785*
							(.932)	(.931)	(.932)	(.944)
INTERESTRATE								11.906	12.198	22.968
								(8.259)	(8.261)	(42.134)
DDELIST_36									.149	.146
									(.136)	(.135)
_cons	-.003	-.113*	-.211	-.359**	-.263	-.278	-.296	-.335*	-.351*	
	(.035)	(.06)	(.163)	(.168)	(.178)	(.187)	(.187)	(.189)	(.189)	
Observations	350	350	350	350	350	350	350	350	350	350
R-squared	.003	.018	.019	.046	.053	.053	.062	.068	.071	.135
Year dummy	NO	NO	NO	NO	NO	NO	NO	NO	NO	YES

Data on IPOs of financial firms between 2008-2017 from the United States. The dependent variables are the cumulative abnormal returns with the equal-weighted S&P 500 index returns used as benchmark over a 36-month time frame. Elaborations and calculations of the independent variables can be found in chapter 4.2. The data is retrieved from Thomson One, Eikon Datastream and Zephyr.

Standard errors are in parentheses. *** p<.01, ** p<.05, * p<.1.

TABLE E15. OLS REGRESSIONS ON CUMULATIVE ABNORMAL RETURNS (1-YEAR)

								(10)
	MSCI Europe (VW)	MSCI Europe (EW)	STOXX Europe (VW)	STOXX Europe (EW)	NASDAQ 100 (VW)	NASDAQ 100 (EW)	S&P 500 (VW)	S&P 500 (EW)
DFINTECH	.064	.067	.054	.065	-.036	.018	-.035	-.027
	(.067)	(.068)	(.067)	(.068)	(.074)	(.105)	(.074)	(.074)
AGE	-.003	-.001	-.004	-.001	.044**	.067**	.044**	.044**
	(.014)	(.014)	(.014)	(.014)	(.019)	(.027)	(.019)	(.019)
REVENUE	-.003	-.003	-.003	-.003	-.001	-.003	-.004	-.003
	(.008)	(.008)	(.008)	(.008)	(.011)	(.015)	(.011)	(.011)
DVENTCAP	-.051	-.051	-.05	-.053	.103*	.095	.097*	.098*
	(.074)	(.074)	(.073)	(.074)	(.058)	(.073)	(.058)	(.058)
PROCEEDS	-.027**	-.026**	-.028**	-.026**	.016	.013	.017	.018
	(.012)	(.012)	(.012)	(.012)	(.027)	(.036)	(.027)	(.027)
DHQ_UNDRW	.04	.037	.037	.036	-.011	-.042	-.005	-.006
	(.05)	(.05)	(.049)	(.05)	(.061)	(.078)	(.061)	(.061)
INDEX_REGION	-.164	-.16	-.166	-.188	.056	1.755*	.006	.131
	(.525)	(.531)	(.52)	(.529)	(.645)	(.995)	(.645)	(.645)
INTERESTRATE	13.753	19.846*	1.578	19.868*	-.976	12.411	-5.454	-6.21
	(10.063)	(10.176)	(9.967)	(10.139)	(28.762)	(33.072)	(28.777)	(28.774)
DDELIST_36	-.072	-.061	-.072	-.064	.074	.087	.068	.069
	(.063)	(.063)	(.062)	(.063)	(.092)	(.111)	(.092)	(.092)
_cons								
Observations	490	490	490	490	350	241	350	350
R-squared	.12	.124	.065	.102	.102	.085	.116	.1
Year dummy	YES	YES	YES	YES	YES	YES	YES	YES

Data on IPOs of financial firms between 2008-2017 from either the United States or Europe (dependent on the index used as the benchmark return). The dependent variables are the cumulative abnormal returns with the value- and equal-weighted index returns used as benchmark over a 12-month time frame. Elaborations and calculations of the independent variables can be found in chapter 4.2. The data is retrieved from Thomson One, Eikon Datastream and Zephyr. Complete regressions of the analyses can be found hereafter in Appendix E: OLS regressions

Standard errors are in parentheses. *** p<.01, ** p<.05, * p<.1.

TABLE E 16. OLS REGRESSION ON CUMULATIVE ABNORMAL RETURNS

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
	CAR_MS CIEU_V W_12	CAR_MS CIEU_V W_12	CAR_MS CIEU_V W_12	CAR_MS CIEU_V W_12	CAR_MS CIEU_V W_12	CAR_MS CIEU_V W_12	CAR_MS CIEU_V W_12	CAR_MS CIEU_V W_12	CAR_MS CIEU_V W_12	CAR_MS CIEU_V W_12
DFINTECH	.061	.059	.055	.057	.05	.049	.047	.048	.048	.064
	(.067)	(.068)	(.068)	(.068)	(.068)	(.068)	(.068)	(.068)	(.068)	(.067)
AGE		.002	.006	.007	.006	.005	.005	.005	.003	-.003
		(.013)	(.014)	(.014)	(.014)	(.014)	(.014)	(.014)	(.014)	(.014)
REVENUE			-.007	-.008	-.001	-.002	-.003	-.003	-.002	-.003
			(.006)	(.007)	(.008)	(.008)	(.008)	(.008)	(.008)	(.008)
DVENTCAP				-.02	-.013	-.012	-.01	-.009	-.018	-.051
				(.074)	(.074)	(.074)	(.074)	(.075)	(.075)	(.074)
PROCEEDS					-.015	-.017	-.016	-.016	-.019	-.027**
					(.01)	(.011)	(.011)	(.012)	(.012)	(.012)
DHQ_UNDRW						.022	.023	.022	.026	.04
						(.05)	(.05)	(.05)	(.05)	(.05)
INDEX_REGION							-.646	-.631	-.685	-.164
							(.52)	(.525)	(.526)	(.525)
INTERESTRATE								.434	.515	13.753
								(1.872)	(1.872)	(10.063)
DDELIST_36									-.081	-.072
									(.064)	(.063)
_cons	.073***	.069**	.142**	.147**	.144*	.154**	.161**	.156*	.18**	
	(.019)	(.03)	(.072)	(.075)	(.075)	(.078)	(.078)	(.082)	(.084)	
Observations	490	490	490	490	490	490	490	490	490	490
R-squared	.002	.002	.004	.004	.009	.009	.012	.012	.016	.12
Year dummy	NO	NO	NO	NO	NO	NO	NO	NO	NO	YES

Data on IPOs of financial firms between 2008-2017 from Europe. The dependent variables are the cumulative abnormal returns with the value-weighted MSCI Europe index returns used as benchmark over a 12-month time frame. Elaborations and calculations of the independent variables can be found in chapter 4.2. The data is retrieved from Thomson One, Eikon Datastream and Zephyr.

Standard errors are in parentheses. *** p<.01, ** p<.05, * p<.1.

TABLE E 17. OLS REGRESSION ON CUMULATIVE ABNORMAL RETURNS

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
	CAR_MS CIEU_E W_12	CAR_MS CIEU_EW _12	CAR_MS CIEU_EW _12	CAR_MS CIEU_EW _12	CAR_MS CIEU_EW _12	CAR_MS CIEU_EW _12	CAR_MS CIEU_EW _12	CAR_MS CIEU_EW _12	CAR_MS CIEU_EW _12	CAR_MS CIEU_EW _12
DFINTECH	.066	.063	.06	.06	.055	.055	.052	.054	.054	.067
	(.068)	(.068)	(.069)	(.069)	(.069)	(.069)	(.069)	(.069)	(.069)	(.068)
AGE		.004	.008	.008	.008	.007	.007	.007	.005	-.001
		(.013)	(.014)	(.014)	(.014)	(.014)	(.014)	(.014)	(.014)	(.014)
REVENUE			-.006	-.007	-.002	-.002	-.003	-.003	-.002	-.003
			(.007)	(.007)	(.008)	(.008)	(.008)	(.008)	(.008)	(.008)
DVENTCAP				-.014	-.008	-.008	-.006	-.005	-.012	-.051
				(.075)	(.075)	(.076)	(.075)	(.076)	(.076)	(.074)
PROCEEDS					-.012	-.013	-.012	-.011	-.014	-.026**
					(.01)	(.011)	(.011)	(.012)	(.012)	(.012)
DHQ_UNDRW						.013	.013	.012	.016	.037
						(.051)	(.051)	(.051)	(.051)	(.05)
INDEX_REGION							-.687	-.67	-.718	-.16
							(.527)	(.532)	(.533)	(.531)
INTERESTRATE								.493	.565	19.846*
								(1.898)	(1.899)	(10.176)
DDELIST_36									-.071	-.061
									(.065)	(.063)
_cons	.076***	.068**	.132*	.135*	.132*	.138*	.146*	.14*	.161*	
	(.019)	(.031)	(.073)	(.076)	(.076)	(.079)	(.079)	(.083)	(.085)	
Observations	490	490	490	490	490	490	490	490	490	490
R-squared	.002	.002	.004	.004	.007	.007	.01	.011	.013	.124
Year dummy	NO	NO	NO	NO	NO	NO	NO	NO	NO	YES

Data on IPOs of financial firms between 2008-2017 from Europe. The dependent variables are the cumulative abnormal returns with the equal-weighted MSCI Europe index returns used as benchmark over a 12-month time frame. Elaborations and calculations of the independent variables can be found in chapter 4.2. The data is retrieved from Thomson One, Eikon Datastream and Zephyr.

Standard errors are in parentheses. *** p<.01, ** p<.05, * p<.1.

TABLE E 18. OLS REGRESSION ON CUMULATIVE ABNORMAL RETURNS

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
	CAR_STOXX_VW_12	CAR_STOXX_VW_12	CAR_STOXX_VW_12	CAR_STOXX_VW_12	CAR_STOXX_VW_12	CAR_STOXX_VW_12	CAR_STOXX_VW_12	CAR_STOXX_VW_12	CAR_STOXX_VW_12	CAR_STOXX_VW_12
DFINTECH	.066	.068	.064	.066	.057	.056	.055	.052	.052	.054
	(.065)	(.066)	(.066)	(.066)	(.066)	(.066)	(.066)	(.066)	(.066)	(.067)
AGE		-.002	.002	.002	.001	.001	0	.001	-.001	-.004
		(.013)	(.013)	(.013)	(.013)	(.013)	(.013)	(.014)	(.014)	(.014)
REVENUE			-.008	-.008	0	-.001	-.001	-.001	-.001	-.003
			(.006)	(.006)	(.008)	(.008)	(.008)	(.008)	(.008)	(.008)
DVENTCAP				-.032	-.022	-.021	-.02	-.023	-.032	-.05
				(.072)	(.072)	(.072)	(.072)	(.073)	(.073)	(.073)
PROCEEDS					-.02**	-.022**	-.022**	-.023**	-.027**	-.028**
					(.01)	(.011)	(.011)	(.011)	(.012)	(.012)
DHQ_UNDRW						.021	.021	.024	.028	.037
						(.049)	(.049)	(.049)	(.049)	(.049)
INDEX_REGION							-.364	-.401	-.458	-.166
							(.505)	(.51)	(.511)	(.52)
INTERESTRATE								-1.033	-.948	1.578
								(1.819)	(1.818)	(9.967)
DDELIST_36									-.084	-.072
									(.062)	(.062)
_cons	.037**	.041	.12*	.128*	.123*	.133*	.137*	.15*	.174**	
	(.019)	(.03)	(.07)	(.073)	(.072)	(.076)	(.076)	(.079)	(.081)	
Observations	490	490	490	490	490	490	490	490	490	490
R-squared	.002	.002	.005	.006	.014	.015	.016	.016	.02	.065
Year dummy	NO	NO	NO	NO	NO	NO	NO	NO	NO	YES

Data on IPOs of financial firms between 2008-2017 from Europe. The dependent variables are the cumulative abnormal returns with the value-weighted STOXX- 600 Europe index returns used as benchmark over a 12-month time frame. Elaborations and calculations of the independent variables can be found in chapter 4.2. The data is retrieved from Thomson One, Eikon Datastream and Zephyr.

Standard errors are in parentheses. *** p<.01, ** p<.05, * p<.1.

TABLE E 19. OLS REGRESSION ON CUMULATIVE ABNORMAL RETURNS

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
	CAR_STOXX_EW_12	CAR_STOXX_EW_12	CAR_STOXX_EW_12	CAR_STOXX_EW_12	CAR_STOXX_EW_12	CAR_STOXX_EW_12	CAR_STOXX_EW_12	CAR_STOXX_EW_12	CAR_STOXX_EW_12	CAR_STOXX_EW_12
DFINTECH	.064	.061	.057	.058	.052	.052	.049	.05	.05	.065
	(.067)	(.068)	(.068)	(.068)	(.069)	(.069)	(.069)	(.069)	(.069)	(.068)
AGE		.004	.008	.009	.008	.007	.007	.007	.006	-.001
		(.013)	(.014)	(.014)	(.014)	(.014)	(.014)	(.014)	(.014)	(.014)
REVENUE			-.007	-.008	-.002	-.003	-.003	-.003	-.003	-.003
			(.007)	(.007)	(.008)	(.008)	(.008)	(.008)	(.008)	(.008)
DVENTCAP				-.021	-.015	-.014	-.012	-.011	-.019	-.053
				(.075)	(.075)	(.075)	(.075)	(.075)	(.075)	(.074)
PROCEEDS					-.013	-.014	-.014	-.013	-.016	-.026**
					(.01)	(.011)	(.011)	(.012)	(.012)	(.012)
DHQ_UNDRW						.013	.014	.013	.017	.036
						(.05)	(.05)	(.051)	(.051)	(.05)
INDEX_REGION							-.698	-.682	-.733	-.188
							(.524)	(.528)	(.53)	(.529)
INTERESTRATE								.44	.516	19.868*
								(1.886)	(1.886)	(10.139)
DDELIST_36									-.075	-.064
									(.064)	(.063)
_cons	.049**	.041	.116	.121	.118	.124	.132*	.127	.148*	
	(.019)	(.031)	(.073)	(.075)	(.075)	(.079)	(.079)	(.082)	(.084)	
Observations	490	490	490	490	490	490	490	490	490	490
R-squared	.002	.002	.005	.005	.008	.008	.012	.012	.015	.102
Year dummy	NO	NO	NO	NO	NO	NO	NO	NO	NO	YES

Data on IPOs of financial firms between 2008-2017 from Europe. The dependent variables are the cumulative abnormal returns with the equal-weighted STOXX- 600 Europe index returns used as benchmark over a 12-month time frame. Elaborations and calculations of the independent variables can be found in chapter 4.2. The data is retrieved from Thomson One, Eikon Datastream and Zephyr.

Standard errors are in parentheses. *** p<.01, ** p<.05, * p<.1.

TABLE E 20. OLS REGRESSION ON CUMULATIVE ABNORMAL RETURNS

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
	CAR_NSDQ100_VW_12	CAR_NSDQ100_VW_12	CAR_NSDQ100_VW_12	CAR_NSDQ100_VW_12	CAR_NSDQ100_VW_12	CAR_NSDQ100_VW_12	CAR_NSDQ100_VW_12	CAR_NSDQ100_VW_12	CAR_NSDQ100_VW_12	CAR_NSDQ100_VW_12
DFINTECH	-.006	-.019	-.017	-.054	-.055	-.056	-.054	-.048	-.049	-.036
	(.071)	(.071)	(.071)	(.074)	(.074)	(.075)	(.075)	(.075)	(.075)	(.074)
AGE		.038**	.039**	.034*	.035*	.035*	.035*	.035*	.034*	.044**
		(.018)	(.018)	(.019)	(.019)	(.019)	(.019)	(.019)	(.019)	(.019)
REVENUE			-.001	.003	0	0	0	0	0	-.001
			(.009)	(.01)	(.011)	(.012)	(.012)	(.012)	(.012)	(.011)
DVENTCAP				.096*	.095*	.094	.094	.097*	.098*	.103*
				(.056)	(.056)	(.059)	(.059)	(.059)	(.059)	(.058)
PROCEEDS					.01	.009	.009	.009	.011	.016
					(.023)	(.027)	(.027)	(.027)	(.027)	(.027)
DHQ_UNDRW						.004	.002	-.006	-.01	-.011
						(.06)	(.06)	(.06)	(.061)	(.061)
INDEX_REGION							.278	.248	.221	.056
							(.636)	(.635)	(.636)	(.645)
INTERESTRATE								8.769	8.924	-.976
								(5.634)	(5.639)	(28.762)
DDELIST_36									.079	.074
									(.093)	(.092)
_cons	-.029	-.098**	-.084	-.138	-.156	-.154	-.157	-.185	-.194	
	(.023)	(.04)	(.11)	(.114)	(.121)	(.127)	(.128)	(.129)	(.129)	
Observations	350	350	350	350	350	350	350	350	350	350
R-squared	0	.013	.013	.021	.022	.022	.022	.029	.031	.102
Year dummy	NO	NO	NO	NO	NO	NO	NO	NO	NO	YES

Data on IPOs of financial firms between 2008-2017 from the United States. The dependent variables are the cumulative abnormal returns with the value-weighted NASDAQ-100 index returns used as benchmark over a 12-month time frame. Elaborations and calculations of the independent variables can be found in chapter 4.2. The data is retrieved from Thomson One, Eikon Datastream and Zephyr.

Standard errors are in parentheses. *** p<.01, ** p<.05, * p<.1.

TABLE E 21. OLS REGRESSION ON CUMULATIVE ABNORMAL RETURNS

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
	CAR_NSDQ100_EW_12	CAR_NSDQ100_EW_12	CAR_NSDQ100_EW_12	CAR_NSDQ100_EW_12	CAR_NSDQ100_EW_12	CAR_NSDQ100_EW_12	CAR_NSDQ100_EW_12	CAR_NSDQ100_EW_12	CAR_NSDQ100_EW_12	CAR_NSDQ100_EW_12
DFINTECH	.026	.025	.031	.008	.007	.01	.016	.025	.019	.018
	(.102)	(.1)	(.101)	(.103)	(.103)	(.104)	(.104)	(.104)	(.105)	(.105)
AGE		.074***	.075***	.067**	.068**	.067**	.069***	.068**	.066**	.067**
		(.025)	(.025)	(.026)	(.026)	(.027)	(.026)	(.026)	(.027)	(.027)
REVENUE			-.005	-.001	-.003	-.003	-.002	-.002	-.002	-.003
			(.012)	(.012)	(.015)	(.015)	(.015)	(.015)	(.015)	(.015)
DVENTCAP				.082	.081	.085	.084	.087	.088	.095
				(.07)	(.07)	(.073)	(.072)	(.073)	(.073)	(.073)
PROCEEDS					.006	.01	.002	.007	.01	.013
					(.029)	(.035)	(.035)	(.035)	(.036)	(.036)
DHQ_UNDRW						-.018	-.016	-.029	-.034	-.042
						(.075)	(.075)	(.076)	(.077)	(.078)
INDEX_REGION							1.773*	1.689*	1.657*	1.755*
							(.929)	(.933)	(.936)	(.995)
INTERESTRATE								6.945	7.25	12.411
								(7.565)	(7.586)	(33.072)
DDELIST_36									.077	.087
									(.11)	(.111)
_cons	.025	-.107**	-.048	-.097	-.107	-.118	-.12	-.151	-.161	
	(.029)	(.054)	(.136)	(.142)	(.15)	(.158)	(.157)	(.161)	(.162)	
Observations	241	241	241	241	241	241	241	241	241	241
R-squared	0	.035	.036	.041	.041	.042	.056	.06	.062	.085
Year dummy	NO	NO	NO	NO	NO	NO	NO	NO	NO	YES

Data on IPOs of financial firms between 2008-2017 from the United States. The dependent variables are the cumulative abnormal returns with the equal-weighted NASDAQ-100 index returns used as benchmark over a 12-month time frame. Elaborations and calculations of the independent variables can be found in chapter 4.2. The data is retrieved from Thomson One, Eikon Datastream and Zephyr.

Standard errors are in parentheses. *** p<.01, ** p<.05, * p<.1.

TABLE E 22. OLS REGRESSION ON CUMULATIVE ABNORMAL RETURNS

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
	CAR_SP_ VW_12	CAR_SP_ VW_12	CAR_SP_ VW_12	CAR_SP_ VW_12	CAR_SP_ VW_12	CAR_SP_ VW_12	CAR_SP_ VW_12	CAR_SP_ VW_12	CAR_SP_ VW_12	CAR_SP_ VW_12
DFINTECH	-.008	-.022	-.019	-.058	-.059	-.06	-.058	-.049	-.05	-.035
	(.071)	(.071)	(.071)	(.074)	(.074)	(.075)	(.075)	(.075)	(.075)	(.074)
AGE		.041**	.042**	.036*	.038**	.038**	.038**	.038**	.038**	.044**
		(.018)	(.018)	(.019)	(.019)	(.019)	(.019)	(.019)	(.019)	(.019)
REVENUE			-.003	.001	-.003	-.003	-.003	-.002	-.002	-.004
			(.009)	(.01)	(.011)	(.012)	(.012)	(.011)	(.011)	(.011)
DVENTCAP				.101*	.1*	.098*	.098*	.105*	.105*	.097*
				(.056)	(.056)	(.059)	(.059)	(.058)	(.058)	(.058)
PROCEEDS					.014	.013	.012	.014	.015	.017
					(.023)	(.027)	(.027)	(.027)	(.027)	(.027)
DHQ_UNDRW						.004	.002	-.011	-.013	-.005
						(.06)	(.06)	(.06)	(.06)	(.061)
INDEX_REGION							.226	.175	.155	.006
							(.637)	(.631)	(.633)	(.645)
INTERESTRATE								15.047***	15.16***	-5.454
								(5.601)	(5.609)	(28.777)
DDELIST_36									.058	.068
									(.092)	(.092)
_cons	.054**	-.021	.015	-.043	-.067	-.064	-.067	-.116	-.122	
	(.023)	(.04)	(.11)	(.114)	(.121)	(.127)	(.128)	(.128)	(.129)	
Observations	350	350	350	350	350	350	350	350	350	350
R-squared	0	.014	.015	.024	.025	.025	.025	.046	.047	.116
Year dummy	NO	NO	NO	NO	NO	NO	NO	NO	NO	YES

Data on IPOs of financial firms between 2008-2017 from the United States. The dependent variables are the cumulative abnormal returns with the value-weighted S&P 500 index returns used as benchmark over a 12-month time frame. Elaborations and calculations of the independent variables can be found in chapter 4.2. The data is retrieved from Thomson One, Eikon Datastream and Zephyr.

Standard errors are in parentheses. *** p<.01, ** p<.05, * p<.1.

TABLE E 23. OLS REGRESSION ON CUMULATIVE ABNORMAL RETURNS

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
	CAR_SP_ EW_12	CAR_SP_ EW_12	CAR_SP_ EW_12	CAR_SP_ EW_12	CAR_SP_ EW_12	CAR_SP_ EW_12	CAR_SP_ EW_12	CAR_SP_ EW_12	CAR_SP_ EW_12	CAR_SP_ EW_12
DFINTECH	-.003	-.017	-.014	-.053	-.054	-.054	-.052	-.044	-.045	-.027
	(.071)	(.071)	(.071)	(.074)	(.074)	(.075)	(.075)	(.075)	(.075)	(.074)
AGE		.042**	.042**	.037**	.038**	.038**	.038**	.038**	.038**	.044**
		(.018)	(.018)	(.018)	(.019)	(.019)	(.019)	(.019)	(.019)	(.019)
REVENUE			-.003	.001	-.003	-.003	-.003	-.002	-.002	-.003
			(.009)	(.01)	(.011)	(.011)	(.012)	(.011)	(.011)	(.011)
DVENTCAP				.102*	.101*	.101*	.1*	.106*	.106*	.098*
				(.056)	(.056)	(.059)	(.059)	(.058)	(.058)	(.058)
PROCEEDS					.013	.013	.013	.014	.015	.018
					(.023)	(.027)	(.027)	(.027)	(.027)	(.027)
DHQ_UNDRW						0	-.002	-.013	-.016	-.006
						(.06)	(.06)	(.06)	(.06)	(.061)
INDEX_REGION							.289	.245	.223	.131
							(.635)	(.631)	(.633)	(.645)
INTERESTRATE								13.004**	13.127**	-6.21
								(5.602)	(5.61)	(28.774)
DDELIST_36									.062	.069
									(.092)	(.092)
_cons	.023	-.052	-.014	-.072	-.095	-.095	-.098	-.14	-.147	
	(.023)	(.04)	(.11)	(.114)	(.121)	(.127)	(.128)	(.128)	(.129)	
Observations	350	350	350	350	350	350	350	350	350	350
R-squared	0	.015	.015	.024	.025	.025	.026	.041	.042	.1
Year dummy	NO	NO	NO	NO	NO	NO	NO	NO	NO	YES

Data on IPOs of financial firms between 2008-2017 from the United States. The dependent variables are the cumulative abnormal returns with the equal-weighted S&P 500 index returns used as benchmark over a 12-month time frame. Elaborations and calculations of the independent variables can be found in chapter 4.2. The data is retrieved from Thomson One, Eikon Datastream and Zephyr.

Standard errors are in parentheses. *** p<.01, ** p<.05, * p<.1.