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A comparative study of the valuation of FinTech and Dot-Com companies

by

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Abstract

This master thesis examines the valuation of FinTech and Dot-Com companies by looking at the underpricing level of initial public offerings (IPOs) and the abnormal returns during the period surrounding the announcement date of merger and acquisitions (M&As). The sample consists of 234 IPO's observations from 1995-2019 and 58 M&A's deals from 2000-2019. The results suggest that the underpricing level of FinTech IPOs is less than the underpricing level of Dot-Com IPOs. As for M&As, univariate testing shows no difference between cumulative abnormal returns (CAR) of FinTech and Dot-Com companies. However, the regression results show higher CAR during the Dot-Com bubble burst (2000). Other variables affecting underpricing level (size, age, expenses, US listed and underwriter reputation) and CAR (size, method of payment, industry, leverage, and advisor ranking) are also examined further in this thesis. For IPOs underpricing, the results show that firm age has a negative relationship with the underpricing level, in contrast with market capitalization. For M&As the method of payment has a negative relationship with the CAR.

Keywords: Initial Public Offering, Merger and Acquisition, FinTech, Dot-Com, Underpricing, Abnormal Return

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Contents

1. Introduction

Financial Technologies (FinTech) industry has grown to become one of the most important industries in today's world. The term FinTech is various according to different business contexts (Schueffe, 2016). There is still no clear definition of FinTech, however, in general, FinTech refers to a company that mainly develops or uses technology in order to provide financial products or services (Varga, 2017). This term is not limited to any specific business sectors, such as financial sectors; it refers to all the financial products and services that are provided by any sector (Arner et al., 2016).

There has been a long history regarding the development of FinTech. However, the Global Financial Crisis in 2008 was the main impact on what made FinTech evolve to become what it is today (Arner et al., 2016). Because of the financial crisis, people had lowered their trust in banks. This led to the emergence of financial innovations and increased number of FinTech companies. These FinTech companies allowed people to easily access loans and increase their investment opportunities (Amalia, 2016). On the other hand, this represented a challenge that banks and financial regulators had to face. Therefore, in addition to pure competitive motivations, many banks and financial regulators try to acquire FinTech companies ever since, in order for them to use FinTech to regain trust of their customers and also to help manage and balance the potential benefits and risks of each financial transaction. This leads to high numbers of FinTech companies acquisitions (Curran, 2016).

As a fast growing industry, raising capital in order to make future investment is very important. Therefore, many FinTech firms around the world choose to go public to gain more capital, meaning that there is a high number of new FinTech IPOs every year. IPO is an abbreviation for the act of the first initial public offering of shares of a company.

Since 2005, FinTech IPO has raised USD 64 billion in the US market, with the amount of approximately USD 7 billion raised in 2018 alone (McLaughlin, 2019). The highest amount raised was in 2008 when Visa Inc. went public. The company alone raised USD 17.9 billion, which is one of the largest IPO in the record of US stock market (Zuill, 2008).

Chinese FinTech firms are also growing in number. According to a research form JP Morgan, the FinTech market in China is expected to gain revenue of USD 69 billion by 2020, with a compound annual growth rate of 44 percent from 2016 to 2020 (He, 2017). Because of this fast growth, most of FinTech companies are expected to go public in both home and overseas stock markets, particularly Hong Kong and the US stock markets (Ren, 2017). In 2018, Chinese FinTech companies accounted for 57 percent of total Chinese IPOs in US (Xueqing, 2018).

As a matter of fact, the investment in FinTech has doubled in 2018 compared to 2017, reaching approximately USD 111.8 billion globally, where almost half of the investment was from the FinTech companies in the United States (KPMG, 2019).

Based on the previous studies about the FinTech IPOs, although very few in number, most of them found that FinTech IPOs are generally underpriced. Underpricing is a stylized fact that states the percentage difference between first day closing price and the offering price of the IPOs, thus, underpricing means this difference is positive. For example, the issuing price for Visa IPO was USD 44 and their first day closing price was USD 56.5, which shows that the IPO was underpriced (Reiche, 2015). Also in 2015, Square Inc, one of the US FinTech companies, went public and their IPO realized around 45 percent increase from their initial offering price (Isaac and Picker, 2015).

According to reports by two of the Big Fours auditors KPMG and PwC, FinTech companies have received outstanding attention and investment in the past years. In 2018, only the first half of the year was enough for setting a new record of USD 41.7 billion invested across 789 deals. The same year UK and US led the way with USD 16.1 billion and USD 14.2 billion dollars invested in FinTech, again, only the first half of the year. UK was also the home of the 4 out of 10 largest FinTech deals during that period. Numerous reports point out that more than half of the financial institutions have put the technological component as a main part of their corporate strategy, with 82% expecting to increase FinTech partnerships between 2018 and 2023 (KPMG, 2019).

Valuation of FinTech is an interesting topic to study, however, first of all let's define what a control group is: a control group is used as a baseline measure and it is identical to all other items or subjects that we are examining with the exception that it does not receive the treatment or the experimental manipulation that the treatment group receives. In our case, as mentioned earlier, since 2008 the global investment in FinTech has increased rapidly. With regard to that, growing popularity of FinTechs has initiated an ongoing discussion that the situation is similar to the period before the occurring of the internet bubble. Thus, we decide to use internet companies as our control group. Moreover, the internet companies that went public at the turn of the century, are identical to FinTech companies in the sense that both have the digital component. So, even though, there is still no established definition of FinTechs, it is fair to at least consider FinTechs as technological companies who offer financial services. This led to the development of the purpose of this paper.

Purpose of the thesis

The aim of the research on this paper is to make a comparative study of the valuation of FinTech and Dot-Com companies.

Accordingly, since abnormal returns to target and IPO underpricing are both possible indicators of "overvaluation" and the dot-com companies are widely regarded as overvalued (Martin & Kemper, 2015), the research will be done by looking at two types of corporate transactions: IPO and M&A. IPOs underpricing and target abnormal return can be used as an indication of the value of the companies since as mentioned, the dot-com companies are widely viewed as overvalued (Martin & Kemper, 2015).

Specifically, the research examines the underpricing of IPOs of FinTech and internet companies from all over the world, the majority being US. The sample period is fairly recent for FinTechs IPOs as they are new in the sense that they have gained tremendous popularity largely after the last decade's financial crisis even though hybrids of financial services platforms and technology have existed since the 1990s. However, for internet companies the data consist of the IPOs during the Dot-Com bubble.

As for M&As, the sample of deals of FinTech and Dot-Com companies includes data from 2000 to 2019.

Structure of the thesis

In the following section, some background regarding FinTech and Dot-Com companies is provided. Next, literature review and empirical evidence is reviewed, followed by data and methodology. The final part covers the regression results alongside with the analysis. Finally, the thesis concludes with the limitations and inference about the overall output of the research.

2. Literature review

2.1 Background

2.1.1 FinTech

Definition

Even though there is no clear definition of FinTech, according to Kagan (2019) FinTech can be defined as:

"FinTech is used to describe new tech that seeks to improve and automate the delivery and use of financial services.The term was initially applied to technology employed at the back-end systems of established financial institutions. FinTech now includes different sectors and industries such as education, retail banking, fundraising and nonprofit, and investment management to name a few."

Transitioning from traditional to digital

The traditional banking system has been one of the main subsets through which the financial industry has run its activity. However, innovation in technology has undeniably affected it like every other major sector of the economy. Its ongoing transformative nature has had its fair share of contribution in the changes that the financial industry has experienced, predominantly in the past 2 decades (Gomber, et al., 2018)

Services and activities such as crowdfunding, peer-to-peer or business-to-business payments and lending have been transformed into digital, online activities which require only internet connection, no physical exchange and much less time than in the traditional way through the banking system. Moreover, FinTechs are helping to remove the barrier and the poor service received by many people in developing economies, as well as make it easier for small businesses to thrive in developed countries (Blakstad & Allen, 2018).

Categories of FinTech

According to a survey by PwC (2016), the financial landscape will continue to change. They argue that the FinTech will become even more fully embedded in the financial services in the years to come, slowly turning into the go-to new model approach in the industry. It goes on to add that Blockchain will further expand beyond cryptocurrency applications and regulators will gradually become as involved with FinTech as the firms they supervise. Since there is still no clear definition of FinTech, there are also many ways to categorise FinTech. The following are the major categories of FinTech:

Money transfer and payments

Money transfer and payments are one of the most important categories of FinTechs market. This category is the largest type of FinTechs. The value of digital payments worldwide are accounting to more than USD 4 trillion (Statista, 2019). This type of FinTech has been used all the time. Because of FinTech, nowadays, consumers can transfer money 24/7. In addition, with the use of technology, there is more cost efficiency, which leads to lowering the fees in transferring the money. Moreover, FinTech allows companies to make international payments online with more cost efficiency than what the traditional banks can offer (Gakman, 2017).

Insurance

There is an increasing number of modern insurance companies that use application to reach to their customers. This type of insurance companies provide more flexibility to the customers than the traditional insurance companies (Zavgorodnya, 2018). According to Ernst & Young (2019), the adaptation of the use of the Internet of Things (IoT), mobile software, Robotic Process Automation (RPA), data science and other digital solution has become a trend for insurance companies. All these changes and development are to enhance their customers experience and cost saving. However, since the insurance market is a highly regulated market, FinTech firms in this market still tend to partner with traditional insurance companies (Gakman, 2017).

Borrowing/Lending

FinTech allows the process of lending and borrowing money to be easily done online. Customers no longer need to turn to the bank or credit union in order to get loans (Gakman, 2017). With the development of lending platform, financial companies are able to use technology to automate and fasten their decision process, as leaders have easier access to borrowers' creditworthiness. This also helps reduce costs as well (Zavgorodnya,2018).

Personal Finance

In the past, in order to get financial advice, customers needed to go to the bank to seek advice from financial advisors. Also, in order to do the budget, spreadsheets or an envelope system needed to be used. However, now, there are many applications that offer customers financial advice and help with budgeting (Gakman, 2017).

Investments

FinTech makes it easier for investors to invest. It provides platform that consumers can hold and manage all their assets in a single place. Financial instruments can be sold and bought through the internet (Tokareva, 2018).

Equity Financing

FinTech companies in this category favor the businesses in terms of raising money. Some of these work as an intermediary in connecting investors with startups. Crowdfunding model and virtual fundraising are also being used in order for helping the business to easily raise funds, as everything can be done through the internet (Gakman, 2017).

Consumer banking

FinTechs consumer banking also represent an alternative to traditional banks for consumers who cannot easily - or at all- get approval for a credit card. As these consumers can use prepaid card offered by these companies. This type of companies is also gaining popularity because they do not charge for high fees, in contrast to traditional banks (Gakman, 2017).

2.1.2 Dot-Com bubble

Dot-Com bubble was a period during the late 1990s where investments in internet-based companies in the U.S. during bull market caused rapid increase in equity valuation of these technology related stocks. During the Dot-Com bubble, the value of the equity markets increased drastically (Hayes, 2019). More than half of the IPOs during 1999 belong to the internet related companies. On the 10th of March, 2000, the Nasdaq index reached its peak at 5048, nearly double the points of the previous year (Kozmetsky & Yue, 2005). This is where the burst began. Due to the peak, there had been high sell orders on stocks of the several leading internet companies such as Dell and Cisco, started by the firms themselves. This caused panic among the investors so they were also selling their own shares. The value of the stock market decreased around 10 percent within a few weeks (Hayes, 2019). By the end of 2001, the majority of the Dot-Com companies that traded in the stock market disappeared. The 2000 bubble burst led the equities market to the downturn, resulting in bankruptcy for several internet companies. The share prices of the companies that survived went down more than 80 percent of their value (Kleinbard, 2000).

2.2 Initial Public Offering

Initial Public Offering (IPO) is the act of private companies going public by issuing their stocks and selling them to the public. The companies go public in order to raise capital in funding for their future investments that aim for the company's future growth (Ljungqvist, 2007). Therefore, when the company issues the price for their stocks, they aim for the highest price possible, in order for them to raise the most capital. On the other hand, the underwriters who submit the shares to the market would consider lower prices as there will be higher possibility for them to sell more shares, thus, gain more profit from the trading expenses.

2.2.1 Underpricing

IPOs underpricing is the finding that the IPO's offered price is lower than its market value. Precisely, it is the case when the issuing price is lower than the first day traded price.

Throughout history, there have been many studies and theories regarding the IPOs' underpricing. The dynamics of this phenomenon, with levels ranging from 16% in 1960 up to 21% in the 1990's and all the way up to 40% during the dot-com bubble, has made it one of the most thought provoking phenomenon in economic literature (Ljungqvist, 2007).

According to Ljungqvist (2007), there are four broad groups of underpricing theories: asymmetric information, institutional reasons, control considerations, and behavioral approaches. However, we only focus on asymmetric information theories as they are more well established, and also behavioural approach theory since this approach is related to the companies being overvalued.

Asymmetric Information

Asymmetric information is based on the assumption of who has more information advantages. The investment bankers have more information about the market demand than the issuer. In addition, since they want to reach the optimal selling of the IPO stocks, they use this advantage to reduce the IPO price to be lower than their market value, which is the reason for IPO underpricing (Baron, 1982). On the other hand, the issuer has better information to justify the true values for their IPOs. Therefore, they might use underpricing as a signal to the investors regarding their quality (Welch, 1989). Precisely, some companies sell their IPOs at a discount in order to show that their company quality is "good" since only good firms are able to maintain their positive returns in the long run. Thus, this will attract more investors to buy their stocks (Ibbotson & Jaffe, 1975).

There is also the well known winner's curse model, where the assumption is that there is asymmetric information between investors. Some investors are informed about the fair value of the IPOs while some are not. The informed investors, then, can avoid investing in the IPOs that are overvalued, unlike uninformed investors (Rock, 1986).

Winner's Curse

The winner's curse of Rock (1986), refers to asymmetric information between informed and uninformed investors. As mentioned earlier, the informed investors are those who have better information about the firms and the fair value of the IPOs. This allows informed investors to distinguish between IPOs that are profitable (underpriced) and IPOs that are unprofitable (overpriced). Thus, these investors will only bid for the shares that are underpriced. Unlike informed investors, uninformed investors do not have better knowledge about the firms and the fair price of the firms. Therefore, they will bid for both IPOs that issued with a higher and also lower price than the fair price. As a result, these uninformed investors will then be placed with a winner's curse as they will receive more or almost only overpriced shares. This is because the informed investors will only bid for underpriced shares, so the allocation for the overpriced shares will go to the uninformed investors only. Consequently, the uninformed investors will most likely receive negative returns, resulting in only informed investors left in the market as it is rational for uninformed investors to never bid for the IPOs again due to their negative expected returns. However, the market cannot survive in these conditions, since institutional investors alone are not enough to supply the market with capital. To adjust the market back to equilibrium, IPOs must be underpriced on average, so that the expected earnings of the uninformed investors are positive or at least break even. Hence, the uninformed investors will still participate in the market.

Behavioural Approaches

Behavioural explanations approach to underpricing argues that the behaviour of the early investors who bid in the IPOs has influenced the decision-making of the other investors. Whatever information that the early investors find out will be passed on to others, and the latter tend to believe in this information and ignore the information that they have. Consequently, the early investor behaviour will be followed. This irrational behaviour will lead to the elastic demand for shares (Welch, 1992). Thus, the underpricing is forced to exist in order to ensure that there will be enough investors' demand in the market.

In addition, behavioural approaches also assume that there is a presence of irrational investors who bid for the IPOs with higher prices than the fair value, and there are behavioral biases that forced underwriter to issue the IPOs with a lower price than their fair value (Ljungqvist, 2007).

Another behavioural explanation of IPOs underpricing is the marketing event. The companies will want their IPOs to have high first day return, therefore, they can achieve high price increases by having underpriced shares. This large price increase can encourage more participants in the market (Maksimovic and Pichler, 2001).

Cyclicality

Ibbotson et al. (1994) suggest that the cyclicality of IPOs occur according to the temperature of the market. During "hot market", the IPOs can be sold with high issuing price. This increases the number of IPOs, and increases the willingness to issue IPOs that are underpriced. If investors are being optimistic about the companies going public, large cycle of volume might occur as the issuer will try to increase their numbers of IPOs to take advantage of the investor's sentiment swing. If the companies are taking advantage of the overvaluation of the market, then the poor performance after the high volume of IPOs are expected (Ibbotson et al., 1994).

2.2.2. Underpricing determinants and empirical evidences

Extensive research on underpricing has brought forward many factors affecting it. Previously mentioned theories and various assumptions about the level of underpricing based on the specific questions at hand, have been translated into observable variables in order to conduct empirical tests. Company characteristics, measures of age, size or the indication of the industry which the company belongs to, have been extensively used as proxies for firm characteristics (Ljungqvist and Wilhelm, 2003; Megginson and Weiss, 1991; and others).

Asymmetric information is related to factors that determine underpricing level. For firm age, younger company will have less historical information in order to use for valuing the companies, which leads to higher level of underpricing (Muscarella and Vetsuypens, 1989). Proceeds, also related to information available as investors are more interested in large IPOs information, which is mostly available only for firms that have higher value of proceeds (Dorsman et al., 2013). Therefore, higher proceed can lead to less underpricing. Another factor that is also related to asymmetric information is firm size, as there is less interest in gathering information for small firms, which leads to higher level of underpricing for smaller firms (Zhang, 2006).

Underpricing during internet bubble can be explained by the behavioural approaches because investors invested heavily in the internet startup companies. The investment in internet stocks became a trend. Because of the overconfidence of the market, investors were willing to overlook the traditional valuations of the companies, and focused their investment on the companies that had triple or quadruple increase in stock prices on their IPOs instead. Therefore, there is high underpricing of the IPOs during this period (Ljungqvist & Wilhelm, 2003).

2.3. Mergers and acquisitions

2.3.1. Abnormal returns determinants and empirical evidence

For various motives, companies engage in different activities of restructuring asset and ownership structures. Although overall there's no strict line dividing different types of corporate deals, in literature we come across mergers, takeovers and buyouts.

Value creation determinants

Various factors are known to contribute in the stock performance of targets of an acquisition. There is a core group that is used in most studies and proves to be informative and significant.

According to Amaro de Matos (2001) whether the target was initially welcoming to the acquisition offer or not, has shown to have a positive effect on target's side.

In general, theories regarding method of payment tend to suggest that equity financed deals generate lower returns for both acquirer and target, respectively. Cash financed deals are linked to better performance compared to equity financed ones. The reasoning behind this is that cash payment sends a signal to the market that the acquirer believes in the target's firm potential or that their own shares are undervalued.

Jensen (1986) on the other hand, adds to this theory by concluding that paying in cash contributes to value creation because it eliminates free cash-flows that could have been used on other unprofitable projects. These findings are also confirmed by Asquith, Bruner, & Mullins (1990), who similarly report that target firms have significantly larger positive abnormal returns with mergers financed with cash than those with stock offers.

In addition, generally, deals that involve parties that belong to different industries are subject to lower returns (Amaro de Matos, 2001). Part of the research done previously has found that merger and acquisition announcements in the same industry have a positive effect on stock return due to expected potential cost synergies and economies of scale.

Leverage can also affect the target return. According to Keehnen (2016), the study of global M&A transactions between 1995-2016, high leverage target firms required higher bid premia. The evidence from the study of 95 stock-for-stock acquisitions also confirmed that the returns of the target firms is positively related to their leverage level (Robinson & Shane, 1990).

There is a lot of research that contributes to the analysis of the effect that size of firm has on the stock performance at announcement date of merger. Although, most of the studies, including those of Moeller et al (2004), focus on the impact on the acquirer's side, numerous others explore the target's stock performance, as well. These documented pieces of evidence suggest that the target firm size can be a proxy of bargaining power during negotiations.

Stylized fact - mergers come in waves

One of the main empirical findings regarding M&A is that there's clustering of merger activity in different industries (Andrade et al., 2001). Many theories suggest that if mergers come in waves that vary quite a lot from one industry to another, this could be due to industry level shocks. That is, industries react to these shocks by merging of companies in order to restructure and adapt to the new business environment.

Shocks could range from technological innovations which can create excess capacity and the need for industry consolidation, deregulation - which can either open new opportunities for investment or remove existing barriers to merging - and supply shocks such as oil prices. Harford (2005), makes a similar argument about merger waves deriving from shocks occurring in different industries at the same time, making mergers more profitable and thus, more attractive.

However, other similar studies add that such shocks cannot have large effects unless accompanied by market misevaluation (Gaughan, 2007).

Empirical evidence in many papers shows that target shareholders are always winners in terms of value received from the mergers with returns ranging from 16%–25% on average (Andrade et al., 2001).

2.4 Hypotheses development

2.4.1 IPOs Underpricing

Previous studies show that there has been a presence of underpricing for Internet and FinTech IPOs. For the Dot-Com IPOs, because of the bubble, we can already confirm that there is underpricing. The evidence is that the underpricing level of IPOs reached the highest during 1999 and 2000, which can be confirmed by the high aggregate amount left on the table, during that time. The aggregate amount left on the table for only these two years is even higher than during that throughout 2001-2018 combined (Ritter, 2018).

As for FinTech IPOs, the research form Sahi (2017) did not reject the hypothesis that US Fintech companies from 2013 to 2016 have an average level of underpricing of 22.64 percent. The existence of underpricing of these companies is also confirmed by the study form Kobeisy (2018), which had done research regarding the underpricing of US FinTech IPOs and found that between January 2005 to July 2017, the average underpricing of US FinTech IPOs is 20.46 percent. According to Steenbergen (2017), who studied the IPO performance of FinTech companies in Europe and North-America between 2005-2017, the result of the study shows significant level of underpricing for both European FinTech IPOs and North-American FinTech IPOs with the level of underpricing of 10 percent and 17 percent respectively.

With regard to evidence from previous studies as well as the fact that the majority of FinTech IPOs are listed in the US stock market (KPMG, 2019) and the dot-com bubble was caused by the technology-related public companies in the US (McCullough, 2018), we have developed the following hypotheses:

Hypothesis 1: Level of IPOs underpricing is higher during the period of dot-com bubble than the period of FinTech boom.

Hypothesis 2: FinTech IPOs dummy variable has negative relationship with the level of underpricing.

Hypothesis 3: US listed IPOs have positive relationship with level of underpricing.

2.4.2 Mergers and acquisitions

Studies find that on average, cumulative abnormal returns are positive for the target. Abnormal returns reflect bid premiums which in turn are higher if the company is overvalued. Since our base assumption is that Fintechs might be overvalued, we expect the abnormal returns to be positive and higher than the observed average.

Moreover, the last two merger waves in which dot-com companies were acquired showed to be correlated with overoptimistic investor sentiment and were classified as "high valuation periods" (Alexandridis, 2012). This gives another incentive to assume that target returns to Fintech companies could be, on average, similar to those of dot-com companies.

In addition, Andrade, Mitchell and Stafford (2001) show that the abnormal returns to target around merger announcement date are stable across decades, despite merger activity.

Following that we develop the following hypothesis.

Hypothesis: Target Fintech companies' cumulative abnormal return is positive and on average, the same as that of Dot-Com companies.

The hypothesis is tested by conducting the Welch test of equality.

3. Data

Due to their existing vaguely specified characteristics and mixed formal indicators about the industries they belong to, compiling the sample for FinTechs was a rather difficult process.

Since FinTech is still a relatively new industry, there is still no clear standard industrial classification in order to distinguish this type of company. In order to select the sample, we follow the list of NASDAQ FinTech provided by Index.co. Afterwards we reassure that the selected companies are under FinTech classification by checking the company's nature of business on by one. If their business belongs to one of the FinTech categories mentioned earlier, then we use that company in our FinTech sample. For the internet companies, we follow the list of Internet IPOs during 1990-2018 provided by Jay R. Ritter. Again, we re-check the company nature of business and eliminate the company that performs business related to financial products and services.

Data sampling is a multilayered process. As a consequence of the nature of the thesis, the steps towards the final data sample were divided into two paths, namely, one aimed at finding listed FinTech and Dot-Com firms and the other at finding the same type of firms that were acquired at some point. Country of origin is not taken into account as the aim is to provide comprehensive results on the type of company of interest, without any geographical restrictions. On the contrary, the goal was to have a diverse country data sample that would enable to see whether the stock market or the country of origin has any effect on the dependent variables.

Information regarding IPOs, on the other hand, was obtained from the NASDAQ, mainly for the company that are listed in the United States, and Bloomberg for the rest of the companies that are not listed in the United States. The information that we retrieved from the mentioned sources are IPOs date, offering prices, number of shares offered, shares outstanding, the name of the stock market that the company was listed in, expenses, name of the lead underwriters and auditor. Sources of closing price on the first day of trading are retrieved from Bloomberg, Thomson Reuters, and Datastream database. Furthermore, news and articles were a good source for missing information on offer price, number of shares offered and shares outstanding. Information about the dates when the companies were founded was either gathered from the websites of the firms themselves, Bloomberg or articles.

Nonetheless, when searching for M&A transactions that had a Dot-Com company as a target, the majority of the deals that came up were done during the so called 6th wave of mergers. This involved the period after the recent "bubble" had burst and companies were recovering, namely during 2000-2007.

As for mergers and acquisitions, the focus was on finding deals in which the target company was either a FinTech company or a Dot-Com in the merger wave at the turn of the century. News and articles were helpful, but the list was mainly compiled by inserting a list of Dot-Com and FinTech companies into the mergers and acquisition database, Zephyr. The results were then filtered manually based on the availability of the historical stock prices for the target, which were then gathered from Thomson Reuters. In some cases, due to lack of data in the previously mentioned sources, Yahoo finance was used as a source for historical stock prices. Zephyr database was also used for data, such as deal value, names of financial advisors, method of payment and merger announcement date. The financial advisors are ranked based on league tables for the corresponding industry and period, available in Zephyr (Allen, et al., 2004).
Using SIC codes (Standard Industrial Classification), we distinguish deals that can be considered more diversifying than others.

The first two digit SIC codes indicate the major group of companies that the company belongs to in the specific industry where the company operates (Andrade, et al., 2001). The second two digits indicate a more narrower classification. Since most of the deals in our sample belong to the same industry in the broad context, we assign a dummy variable that takes value 1 if the targets and acquirers have the same first two digits in their SIC codes.

The initial sample for mergers and acquisition was quite large but, due to missing data or multiple events occurring successively for some companies, the number of deals fell down considerably, with only 58 left in the final sample.

4. Methodology

In order to test for the predefined hypothesis regarding IPO underpricing and abnormal returns to target, we use two different methodological approaches which are IPOs underpricing and event study.

4.1. IPOs Underpricing

Underpricing of IPOs is the percentage difference between first day closing price and the offering price of the IPOs and is calculated by using the following formula:

$$Underpricing = \frac{First\ day\ closing\ price - Offering\ price}{Offering\ price}$$

There are three main models and another extra model including the variable of reputation. The first model is the regression that tests for the effect of the year on the level of underpricing. The regression will only include underpricing as dependent variable and all of the years from 1995 to 2019, except 2000. We are using the year 2000 as our reference year in our model.

Model 1:

$$\begin{aligned} Underpricing = {} & \alpha + \beta_1 * Y\_1995 + \beta_2 * Y\_1996 + \beta_3 * Y\_1997 + \beta_4 * Y\_1998 \\ & + \beta_5 * Y\_1999 + \beta_6 * Y\_2001 + \beta_7 * Y\_2002 + \beta_8 * Y\_2004 + \beta_9 * Y\_2005 \\ & + \beta_{10} * Y\_2006 + \beta_{11} * Y\_2007 + \beta_{12} * Y\_2008 + \beta_{13} * Y\_2009 + \beta_{14} * Y\_2010 \\ & + \beta_{15} * Y\_2011 + \beta_{16} * Y\_2012 + \beta_{17} * Y\_2013 + \beta_{18} * Y\_2014 + \beta_{19} * Y\_2015 \\ & + \beta_{20} * Y\_2016 + \beta_{21} * Y\_2017 + \beta_{22} * Y\_2018 + \beta_{23} * Y\_2019 + \varepsilon_t \end{aligned}$$

The second and the third model are structured to compare how underpricing determinants and time period affect the FinTech and Dot-com IPOs underpricing, in which model 2 is running with only the variables that determine the underpricing level of IPOs. In model 3, we will only add the control variable of the years into the regression.

Model 2:

$$Underpricing \;=\; \alpha + \beta_1 FINTECH + \beta_2 D1_{US\ listed} + \beta_3 * AGE$$
$$+ \beta_4 LN\_MKTCAP + \beta_5 LN\_EXP + \varepsilon_t$$

Model 3:

$$Underpricing \;=\; \alpha + \beta_1 FINTECH + \beta_2 D1_{US\ listed} + \beta_3 AGE$$
$$+ \beta_4 LN\_MKTCAP + \beta_5 LN\_EXP + \beta_6 Y\_1995 + \beta_7 Y\_1996 + \beta_8 Y\_1997$$
$$+ \beta_9 Y\_1998 + \beta_{10} Y\_1999 + \beta_{11} Y\_2001 + \beta_{12} Y\_2002 + \beta_{13} Y\_2004$$
$$+ \beta_{14} Y\_2005 + \beta_{15} Y\_2006 + \beta_{16} Y\_2007 + \beta_{17} Y\_2008 + \beta_{18} Y\_2009$$
$$+ \beta_{19} Y\_2010 + \beta_{20} Y\_2011 + \beta_{21} Y\_2012 + \beta_{22} Y\_2013 + \beta_{23} Y\_2014$$
$$+ \beta_{24} Y\_2015 + \beta_{25} Y\_2016 + \beta_{26} Y\_2017 + \beta_{27} Y\_2018 + \beta_{28} Y\_2019 + \varepsilon_t$$

Model 4:

$$Underpricing \;=\; \alpha + \beta_1 FINTECH + \beta_2 D1_{US\ listed} + \beta_3 AGE$$
$$+ \beta_4 LN\_MKTCAP + \beta_5 LN\_EXP + \beta_6 Y\_1995 + \beta_7 Y\_1996 + \beta_8 Y\_1997$$
$$+ \beta_9 Y\_1998 + \beta_{10} Y\_1999 + \beta_{11} Y\_2001 + \beta_{12} Y\_2002 + \beta_{13} Y\_2004$$
$$+ \beta_{14} Y\_2005 + \beta_{15} Y\_2006 + \beta_{16} Y\_2007 + \beta_{17} Y\_2008 + \beta_{18} Y\_2009$$
$$+ \beta_{19} Y\_2010 + \beta_{20} Y\_2011 + \beta_{21} Y\_2012 + \beta_{22} Y\_2013 + \beta_{23} Y\_2014$$
$$+ \beta_{24} Y\_2015 + \beta_{25} Y\_2016 + \beta_{26} Y\_2017 + \beta_{27} Y\_2018 + \beta_{28} Y\_2019$$
$$+ \beta_{28} REPUTATION + \varepsilon_t$$

Table 1: IPOs regression variables definition

Variable	Definition
UNDERPRICING	The dependent variable refers to the percentage difference between the offering price and the closing price of the first trading day.
FINTECH	An independent variable, which is a dummy variable representing FinTech IPOs, where the value of 1 is taken from the FinTech IPOs, and value of 0 is for Internet firms. (Testing Hypothesis 2)
US	An independent variable, which is a dummy variable refers to the IPOs that listed in the US Stock Exchange. The value of 1 is assigned for the companies that were listed in the US Stock Exchange, and 0 otherwise (Testing Hypothesis 3).
AGE $[ln(1+age)]$	The age of the company is an independent variable, measured by the difference between the company's establishment year and the IPOs year. The natural logarithms of one plus variable is taken. We expect the sign of age to be positive as suggested in the previous studies by Ritter (1991); Megginson and Weiss (1991); Bilson et al., 2003; Ljungqvist and Wilhelm (2003).
LN_MKTCAP	The market capitalization of the company acts as an independent variable in the regression. This variable is measured by the logarithm of the multiplication value between the number of shares outstanding and stock price. Market capitalization represents the size of the company, so we expect negative relationship with the underpricing as

	this is the case in the previous research as well (Otero & González-Méndez, 2006; Loughran and Ritter 2004; Zhang, 2006).
LN_EXP	The expenses is an independent variable referring to the amount of money that company spends mainly on advisors and fees in doing the public offering. The expenses are scaled with proceeds and by taking the natural logarithm. Since previous research suggested that there is a positive relationship between expenses and underpricing Ritter (1987), we expect the same result.
REPUTATION	An independent variable which is a dummy variable that gives the value of 1 if the underwrites has highest reputation ranking, and 0 otherwise. We expect to see negative relationship for this variable as negative relationship was also presented in the previous studies (Cao, 2010; Sharma & Seraphim, 2010; Wang et al. 2003)
Y_XXXX	An independent dummy variable. XXXX refers to the year of IPOs, which in this sample consist of the year between 1995-2019. The value of 1 is taken for the IPOs that listed on the referring year and 0 otherwise.

Table 2: Descriptive statistics of IPOs data

Entire sample						
Variables	**Mean**	**Median**	**Max**	**Min**	**Std. Dev.**	**Obs.**
Underpricing	0.860	0.363	6.056	-0.755	1.067	234
Firm characteristics						
Fintech	0.568	.	.	.	0.496	234
Age	2.109	1.950	9.220	0.000	0.979	234
Ln_mktcap	20.462	20.547	24.068	16.981	1.395	234
IPOs characteristics						
US	0.902	.	.	.	0.298	234
Ln_exp	-3.050	-2.659	-0.966	-10.820	1.245	234
Reputation	0.671	.	.	.	0.471	234

FinTech						Dot-Com					
Mean	**Median**	**Max**	**Min**	**Std. Dev.**	**Obs.**	**Mean**	**Median**	**Max**	**Min**	**Std. Dev.**	**Obs.**
0.191	0.126	3.094	-0.755	0.405	133	1.741	1.521	6.056	0.087	1.030	101
Firm characteristics						Firm characteristics					
.	.	.	.	.	133	.	.	.	.	.	101
2.393	2.400	5.063	0.000	0.890	133	1.734	1.610	9.220	0.000	0.969	101
20.066	20.298	23.951	16.981	1.506	133	20.984	20.930	24.068	18.441	1.028	101
IPOs characteristics						IPOs characteristics					
0.827	.	.	.	0.380	133	.	.	.	.	.	101
-3.298	-2.733	-0.966	-10.820	1.560	133	-2.723	-2.659	-2.524	-6.682	0.459	101
0.632	.	.	.	0.484	133	0.723	.	.	.	0.450	101

4.2. M&A abnormal returns

Evidence related to the performance of the company at merger announcement comes from traditional window event studies. Using average abnormal returns at merger announcement, it can be determined whether the merger has created value or not.

Event study will be used to study abnormal returns for M&A. The abnormal return will be calculated and then using the regression we will test the effect of each factor on the returns.

Estimation of abnormal and normal returns

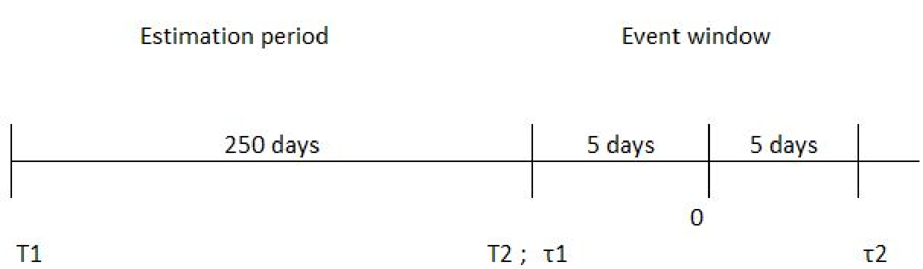
Event study methodology is considered to be quite efficient and easy to interpret MacKinlay (1997).

Essentially, the investigation about the effect of an event (an announcement in this case) on a stock return consists of the calculation and testing of the statistical significance of the abnormal return, around the event date.

The data sample is divided into two periods:

a) The estimation period - the period used to measure the normal return.
b) The event window - the period where abnormal returns are calculated.

The length of these two periods varies among studies. Additionally, some choose to have a gap between the estimation period ending and the event window beginning, others do not.



Following the suggestion of MacKinlay (1997) who argue that in an event study using daily data, the estimation window should include no less than 120 days, in this thesis, the length of the estimation window is 250 days. Essentially, normal returns are estimated using the returns from 255 days to 5 days before the announcement date of the merger.

For the purpose of this estimation, two models are known to be used mainly: constant market return and the market model. The latter is a one factor model that takes into account the correlation of the stock with the market. Hence, this approach is preferred relative to the constant model. The market model return equation is as follows:

$$R_{it} = \alpha_i + \beta_i R_{mt} + \varepsilon_{it} \qquad \ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots....(1)$$

Where:

R_{it} - actual return for stock *i* at time *t* calculated as

$\alpha_{i\ ,}$ - stock specific coefficient : intercept

B - stock specific coefficient : slope i.e., sensitivity to market.

R_{mt} - return on market index , which is chosen depending on the types of companies and geographical characteristics.

ε_{it} - error term for stock *i* at time *t*.

Following equation (1), stock specific regression coefficient estimates are obtained by regressing their returns for the period specified as estimation period with the market index. In this thesis, mainly the S&P 500 was used as the market index since it most of the companies are US based. The return on the index are used in the next step for the calculation of the expected normal return in the event window.

The abnormal return is then calculated as the difference between $R_{it,}$ which is the actual return for stock i at time t, and the expected (normal) return.

$$AR_{it} = R_{it} - (\alpha_i + \beta_i R_m) \qquad \ldots\ldots\ldots\ldots\ldots\ldots\ldots..\ldots\ldots\ldots\ldots\ldots\ldots\ldots.(2)$$

In order to test the effect of the events on the whole sample for the entire event window, we move on to another step that needs to be undertaken. That is the calculation of the CAR - cumulative abnormal return.

The cumulative abnormal return is the sum of all abnormal returns along all the event window.

$$CAR(\tau 1; \tau 2) \sum_{t=\tau 1}^{\tau 2} ARit \text{ ....(3)}$$

It is used to measure the effect the event might have had in the stock performance. In this case in particular, we tested whether the announcement of the acquisition contributes to any abnormal return that we might find to have occurred.

Upon measuring CAR, a significance test is then performed to confirm the reliability of the result.

Specifications

The first model is constructed so that it isolates the effect that different points in time can have on stock performance around announcement date. This is done to provide insight about the effect potential merger waves and hot markets can have on the dependent variable.

Model 1:

$$\begin{aligned} CAR\ (\tau 1;\ \tau 2)\ i\ &= \alpha + \beta_1 Y\_2001 + \beta_2 Y\_2002 + \beta_3 Y\_2003 + \beta_4 Y\_2004 \\ &+ \beta_5 Y\_2005 + \beta_6 Y\_2006 + \beta_7 Y\_2008 + \beta_8 Y\_2009 + \beta_9 Y\_2010 \\ &+ \beta_{10} Y\_2012 + \beta_{11} Y\_2013 + \beta_{12} Y\_2014 + \beta_{13} Y\_2015 + \beta_{14} Y\_2016 \\ &+ \beta_{15} Y\_2017 + \beta_{16} Y\_2018 + \beta_{17} Y\_2019 + \varepsilon_t \end{aligned}$$

Moving on to the second model, the 5-day CAR is regressed against the main independent variables of interest, that is, the FinTech dummy representing these companies and also a number of firm and deal specific variables that empirical evidence suggests as relevant. These variables include method of payment, market capitalization, industry relatedness, alongside leverage as well. The ranking of financial advisor has missing data for a couple of deals, that is why it is not included in model 2, but instead it appears as a regressor in a new specification, namely model 4. Consequently, model 4 is the one where all the deal characteristics are included, but the number of observations is lower.

Model 2:

$$CAR\ (\tau_1; \tau_2)_i = \alpha + \beta_1 FINTECH + \beta_2\ METHOD + \beta_3 INDUSTRY + \beta_4 LN\_MKT + \beta_5 LIAB\_ASSET + \varepsilon_i$$

In model number 3 and 4, year dummy variables are included alongside the deal and firm specific variables. The purpose is to compare how time effects can assist in explaining the CAR of FinTech and Dot-Com companies, respectively.

Model 3:

$$CAR\ (\tau_1; \tau_2)_i = \alpha + \beta_1 FINTECH + \beta_2\ METHOD + \beta_3 INDUSTRY + \beta_4 LN\_MKT + \beta_5 LIAB\_ASSET + Y\_2000 + Y\_2001 + Y\_2002 + Y\_2017 + \varepsilon_i$$

Model 4:

$$CAR\ (\tau_1; \tau_2)_i = \alpha + \beta_1 FINTECH + \beta_2\ METHOD + \beta_3 INDUSTRY + \beta_4 LN\_MKT + \beta_5 LIAB\_ASSET + ADVISOR + Y\_2000 + Y\_2001 + Y\_2002 + Y\_2017 + \varepsilon_i$$

Table 3: M&As regression variables definition

Variable	Definition
CAR	Cumulative abnormal return of target firm is the variable of interest (the dependent variable). The event window consists of 11 days, including the event date.
FINTECH	A dummy variable that takes on value of 1 if the company belongs to the FinTechs sample.
METHOD	A dummy variable that takes value of 1 if the purchase is at least partly financed by equity and zero otherwise.
INDUSTRY	A dummy that takes value of 1 if the companies involved in the transaction have first 2 different digits in their SIC codes.
LN_MKT	The logarithmic value of target's market capitalization at the fiscal year-end prior announcement.
LIAB_ASSET	Total liabilities to total assets ratio at the fiscal year-end prior announcement.
ADVISOR	Highly ranked financial advisor: a dummy variable that takes on a value of 1 if the target's financial advisor is highly ranked, 0 zero otherwise. Allen et al., (2004), analyzed the role of this intermediary that plays a part in the certification effect. They find that deals that have a top-tier financial advisor in either side of the transaction contribute to higher value creation.
Y_XXXX	A dummy variable where XXXX refers to the year of M&As announcement, which in this sample consist of the year between 2000-2019. The value of 1 is taken for the M&A that are announced on the referring year and 0 otherwise.

Table 4: Descriptive statistics of M&As data

Entire sample						
Variables	**Mean**	**Median**	**Max.**	**Min.**	**Std. Dev.**	**Obs.**
CAR(-5;+5)	0.246	0.187	0.925	-0.162	0.225	58
Target characteristics						
Ln of Market cap (bn)	20.097	20.292	23.912	16.76	1.743	58
Leverage	0.323	0.217	1.017	0.034	0.266	58
Deal characteristics						
Equity financed deals	0.362				0.485	58
Related by industry	0.397	.	.	.	0.493	58
Top-tier financial advisor	0.449				0.503	49

FinTech						Dot-Com					
Mean	**Median**	**Max.**	**Min.**	**Std. Dev.**	**Obs.**	**Mean**	**Median**	**Max.**	**Min.**	**Std. Dev.**	**Obs.**
0.246	0.153	0.829	-0.005	0.208	29	0.247	0.199	0.925	-0.162	0.244	29
Target characteristics						Target characteristics					
20.424	20.329	23.912	16.76	1.96	29	19.77	19.671	21.991	17.246	1.456	29
0.367	0.228	1.017	0.036	0.295	29	0.28	0.212	0.949	0.034	0.229	29
Deal characteristics						Deal characteristics					
0.276				0.455	29	0.448				0.506	29
0.517	.	.	.	0.509	29	0.276	.	.	.	0.455	29
0.44				0.507	25	0.667				0.509	24

4.3 Diagnostic testing

For the linear regression, however, before running it, finding and interpreting the level of significance of each independent variable, a few assumptions have to hold (Brooks, 2014).

E(ut) = 0

var(ut) = $\sigma^2 < \infty$

cov (ui , uj) = 0

cov (ut ,xt) = 0

ut ~ N(0 , σ)

First and foremost, the assumption about the mean of the regression residuals have is that it is zero. However, as long as there is an intercept term included, there is no need to test for this as it equals zero by construction in OLS. (Brooks, 2014)

The other assumption is that the variance of the residuals is constant i.e there is homoscedasticity. Multiple tests are available for use, such as that by breusch-Pagan-Godfrey, White's test, Goldfeld-Quandt etc.

Furthermore, if observed collinearity is higher than 0.8 between independent variables , it should be accounted for by taking logarithm or first differencing.

Autocorrelation of residuals can only be a problem if the data is time-series.

Non-normality of the data is also considered as a violation, however, according to the central limit theorem, it is negligible when the sample is large enough (LaMorte, 2016). Nonetheless, it can be accounted for by transforming the variable into natural logarithm, winsorizing, using dummy variables for or removing any outliers that seem to cause the non normality in the first place.

Violation of these assumptions leads to incorrect inference and bias, therefore, they need to be accounted for.

5. Empirical Results & Discussion

5.1 IPOs Underpricing

Table 5: Univariate test results

	FinTech	Internet	Combine	Welch test
Underpricing	19.147%	174.07%	86.017%	
t-statistic	5.455***	16.986***	12.327***	15.821***
Std. Dev.	0.405	1.030	1.067	
Observations	133	101	234	

***significant at 1% level, **significant at 5% level, *significant at 10% level

Table 5 shows that levels of underpricing between FinTech IPOs and Internet IPOs are extremely different. The level of underpricing of Internet IPOs is approximately 155 percent higher than the level of underpricing of FinTech IPOs. This is due to the fact that the sample of dotcom IPOs mainly consist of IPOs during the bubble, which leads to a very high underpricing level. The results also strongly reject the hypothesis of no difference in mean between the two. The test hypothesis is rejected at the 1 percent significance level.

Table 6: Summary of average underpricing

Years	Average Underpricing	Observations
	1995 - 1999	
FinTech	38.29%	6
Dot-com	178.58%	74
Combine	175.78%	80
	2000	
FinTech	50.00%	1
Dot-com	142.71%	27
Combine	139.39%	28
	2001-2007	
FinTech	10.11%	26
	2008-2019	
FinTech	20.12%	100

Table 6 shows the average level of underpricing during each period of time. During the time of the dot-com bubble, 1994-1999, the period consists of 80 IPOs observations in which 74 observations are Internet IPOs and 6 observations are FinTech IPOs. This period has the highest combined average level of underpricing of approximately 176 percent. If we do not take into account the differences in number of observations, the dot-com IPOs during this period are about 140 percent higher than the FinTech IPOs.

During 2000, the time when the bubble burst, the average underpricing is 139 percent, which is the second highest. We have only one sample of FinTech IPOs and 27 dot-com samples in this period. Again, the dot-com IPOs has higher level of underpricing, but at a lower percentage. This is because the bubble burst took place in the first quarter of the year, during March 2000, when the US stock market reached its peak (Whitefoot, 2017). After the bubble burst, the market experienced a downturn, thus the level of underpricing started to decrease.

After the dot-com bubble burst, the average level of underpricing went down drastically to only 10 percent. However, this is with the limitation that the observations during this period and after consist of FinTech companies only. The number of observations is 26 FinTechs IPOs for this period.

During the FinTech boom, starting from 2008, the level of underpricing has increased to almost 21 percent, averaged from 100 FinTech IPOs. Again, if we compare the period of FinTech boom and the period of internet bubble, we can clearly see that the levels of underpricing between these two periods are incomparable. However, FinTech underpricing level in general is still higher than the average overall US underpricing of IPOs between the year 2008-2018 except for 2013, which has the underpricing level of 20.9 percent (Ritter, 2018). As a result, the FinTech IPOs are slightly more underpriced than the overall market.

__Multivariate regression results__

Table 7, Regression results, IPO underpricing

	Model 1		Model 2		Model 3		Model 4	
	Coeff.	Std. Error	Coeff.	Std. Error	Coeff.	Std. Error	Coeff.	Std. Error
Fintech	-	-	-1,334***	0,109	-0,925***	0,277	-0,918***	0,278
US	-	-	-0,347	0,211	-0,271	0,255	-0,268	0,256
Age	-	-	-0,122**	0,051	-0,083	0,053	-0,082	0,053
ln(Market cap)	-	-	0,184***	0,036	0,194***	0,039	0,200***	0,042
ln(Expenses)	-	-	0,045	0,048	0,079	0,048	0,0822*	0,049
1995	-0,314	0,757	-	-	-0,507	0,699	-0,497	0,701
1996	0,145	0,757	-	-	0,138	0,7	0,153	0,702
1997	-0,674**	0,298	-	-	-0,219	0,284	-0,212	0,285
1998	-0,1	0,221	-	-	0,173	0,21	0,17	0,211
1999	0,697***	0,175	-	-	0,694***	0,163	0,696***	0,163
2001	-1,290*	0,757	-	-	-0,3	0,744	-0,335	0,751
2002	-1,499***	0,544	-	-	-0,286	0,57	-0,2755	0,572
2004	-0,804	0,757	-	-	0,3431	0,745	0,357	0,748
2005	-1,358***	0,25	-	-	-0,155	0,352	-0,159	0,353
2006	-1,156***	0,314	-	-	-0,034	0,396	-0,044	0,397
2007	-1,397**	0,544	-	-	-0,179	0,569	-0,189	0,571
2008	-1,073**	0,544	-	-	-0,278	0,574	-0,28	0,575
2009	-1,242**	0,544	-	-	-0,325	0,568	-0,321	0,569
2010	-1,288***	0,265	-	-	-0,173	0,36	-0,178	0,361
2011	-1,242***	0,452	-	-	-0,275	0,494	-0,298	0,498
2012	-1,051***	0,285	-	-	0,081	0,374	0,087	0,375
2013	-1,231***	0,285	-	-	0,048	0,377	0,054	0,378
2014	-1,203***	0,243	-	-	-0,167	0,348	-0,175	0,349
2015	-1,242***	0,257	-	-	-0,071	0,356	-0,07	0,356
2016	-1,314***	0,334	-	-	-0,217	0,414	-0,223	0,415
2017	-1,251***	0,25	-	-	-0,195	0,366	-0,193	0,367
2018	-1,021***	0,238	-	-	0,39	0,391	0,393	0,391
2019	-1,266***	0,397	-	-	-0,028	0,485	-0,034	0,486
Intercept	1,394***	0,14	-1,432*	0,765	-2,053**	0,88	-2,146***	0,913
Reputation	-	-	-	-	-	-	-0,043	0,111
R-squared	0,563		0,575		0,64		0,64	
F-stat.	11,754		61,618		12,989		12,494	
No. of obs.	234		234		234		234	

Note: */**/*** denotes statistical significance at the 10/5/1 percent level

Before commenting on the result, we have performed diagnostic and specification testing for all of our models in order to ensure that the model does not violate assumptions of Ordinary Least Squares regression method.

Heteroscedasticity, normality and the collinearity have been checked. All of our models do not reject the null hypothesis of homoscedasticity except the second model where the null hypothesis is rejected at 5 percent level. Therefore, the White robust standard errors has been used in order to correct the standard error of this model.

Jarque-Bera test of normality of residual is not needed for this data sample as the central limit theorem applies. Also, there is no suspicion of endogeneity between our independent variables, thus, we assume exogeneity for all of our variables. Correlation matrix is also used in order to check for multicollinearity, and we found that near multicollinearity is not a problem for our model.

The first model tests for the effect of the level of underpricing during each year by using the year of 2000, the year of the bubble burst, as our reference year. The result shows that during the bubble, the underpricing level is higher than that during the period after the bubble burst (2001-2007), and also higher than the period after the boom of FinTech (starting from 2008). The results are in line with the statistics provided by Ritter (2018), which shows that the underpricing level of IPOs reached the highest percentage during 1999, in which year our coefficient shows positive sign with the statistical significant level of one percent. In addition, significant negative coefficient appears for all of the years after 2000, except 2004 which has insignificant coefficient. These results confirm our hypothesis that the underpricing level is higher during the period of dot-com bubble than the period of the FinTech boom.

In model 2, which includes variables that are expected to affect underpricing level, the result shows that the dummy variable of FinTech IPOs is significant at one percent level with a negative coefficient sign, meaning that FinTech IPOs are less underpriced than dot-com IPOs, which is consistent with our second hypothesis. Since the period of FinTech companies boom comes after the period of dot-com bubble, the experience from the internet bubble should have given investors and underwriters a lesson. Therefore, they supposedly should have more caution regarding the underpricing problem.

The second hypothesis is also confirmed when adding the control variable of year in Model 3. Similarly, it shows a negative relationship between the dummy variable for FinTech and the level of underpricing, with the significant level of one percent. However, the coefficient of FinTech's dummy is lower when we use the year 2000 as our reference year. This is because the level of underpricing is relatively high during 2000, which is the year that the bubble burst. The only significant year's dummy is the year of 1999, with the significant level of one percent and it has a positive sign of coefficient. This implies that the IPOs during the year of 1999 and 2000 are highly overvalued, especially for the dot-com companies, which is in line with the fact that the highest average level of underpricing falls during 1999 and 2000. The average level of underpricing for 1999 is 73 percent and the average level of underpricing for 2000 is 89 percent. The combined underpricing level of IPOs for these two year is 89 percent (Ljungqvist & Wilhelm, 2003), which is the highest compared with the average underpricing level between 1960-2018 (Ritter, 2018).

Regarding the US listed companies, the results turn out to be insignificant in both model 1 and model 2. Therefore, we are unable to make a conclusion for our third hypothesis, whether US listed IPOs have a positive relationship with level of underpricing or not.

Other determinant variables for underpricing are also included in the regression. One of them is the company age, which refers to the difference between the founding date and IPO date. The results are as we expected: the firm age is negatively related to the IPOs underpricing level. This is explained by theories regarding information asymmetry. Since the value of the younger companies is difficult to estimate due to the lack of information available, underpricing is more likely to be the case (Muscarella and Vetsuypens, 1989). Consistent with other findings from the studies done by Megginson and Weiss (1991), Bilson et al., (2003), and Ljungqvist and Wilhelm (2003), the negative relationship between company age and the underpricing level is present in this sample as well. However, when we also control for the year, with 2000 as reference, the age turns out to be insignificant, with only 1999 significant and 2000 as a reference year this implies that during the period of the peak of Dot-Com bubble, the company age does not explain the level of underpricing.

The size of the company, which is measured by market capitalization, is significant at one percent level, and it has a positive relationship with the level of IPOs underpricing. The results turn out to be opposite from our expectation. Normally, the size of the company should have negative relationship with the underpricing level as large companies are consistently being monitored, and small companies tend to have smaller gains after the IPOs, therefore, there is less interest in gathering information of small firms, and absent of information leads to underpricing (Zhang, 2006).

However, the results are still in line with most of the previous researchers. Some studies found that in regards to the level of underpricing and market capitalization, the relationship between these two turns out to be positive. This is because the companies that have small market capitalization tend to grow with only small profits, which makes it less sensitive to investor sentiment (Baker and Jeffrey, 2006).

We assume that expenses related to going public have positive relationship with underpricing level. However, the results show insignificant coefficient for all models except model 4. In model 4 the coefficient is significant at 10 percent level, and the sign is positive, which is in line with previous research's result done by Ritter (1987) that presented positive relationship between the two.

Lastly, the underwriter reputation is also included as a variable. We expected the underwriter reputation to be negatively related to the underpricing, but again the coefficient shows insignificant coefficient. Therefore, with our sample, results suggested form the previous researches of Wang et al. (2003), Sharma & Seraphim (2010), and Cao (2010) will not be confirmed.

5.2 M&As

Univariate test results

The Cumulative Abnormal Return for both groups of companies results to be statistically significant at all levels.

	FinTech	Internet	Combine	Welch test
CAR	24.618%	24.660%	24.640%	
t-statistic	6.3777***	5.441***	8.381***	0.008
Std. Dev.	0.208	0.244	0.225	
Observations	29	29	58	

***significant at 1% level, **significant at 5% level, *significant at 10% level

Since our aim is to determine whether the market, stock returns in this case, react similarly for both groups, we perform the t-test for two independent means. The test statistic result means that the average cumulative abnormal return for FinTechs is not statistically different from that of Dot-Com companies, considering both of them on the target side of the merger deal.

Refering back to average abnormal return to targets ranging from 16%-25% mentioned in the literature review, it is clear that both groups have a large average which proved to be significant. The average CAR for the Fintech surge in M&A is high, statistically significant and compared to that of the merger wave of dot-com, the null hypothesis of no difference is not rejected.

Multivariate regression results

Following the univariate tests, we go on to conduct a multivariate regression analysis. The preliminary step is to test for possible Ordinary Least Squares assumption violations (Brooks, 2014). Testing for normality is not necessary because the Central Limit Theorem (CLT) applies in samples with observation number higher than 30. Therefore, none of the models violate any of the assumptions.

Table 9. Regression results, 5-day target cumulative abnormal return.

	Model 1		Model 2		Model 3		Model 4	
	Coeff.	Std. Error	Coeff.	Std. Error	Coeff.	Std. Error	Coeff.	Std. Error
Fintech	-	-	-0,022	0,067	0,155	0,075**	0,083	0,081
Method	-	-	-0,133	0,071*	-0,212	0,064***	-0,169	0,067**
Industry	-	-	0,033	0,069	0,039	0,059	0,031	0,063
ln(Market cap)	-	-	-0,001	0,018	-0,017	0,016	0,006	0,018
Leverage	-	-	-0,094	0,114	-0,134	0,098	-0,047	0,116
Advisor	-	-	-	-	-	-	0,052	0,059
2000	-	-	-	-	0,314	0,083***	0,213	0,091
2001	-0,292	0,145*	-	-	-0,088	0,125	-0,029	0,199
2002	-0,444	0,236*	-	-	-0,012	0,210	-0,158	0,214
2003	-0,115	0,236	-	-	-	-	-	-
2004	-0,168	0,119	-	-	-	-	-	-
2005	-0,328	0,236	-	-	-	-	-	-
2006	-0,183	0,172	-	-	-	-	-	-
2008	-0,241	0,172	-	-	-	-	-	-
2009	0,082	0,236	-	-	-	-	-	-
2010	-0,287	0,172	-	-	-	-	-	-
2012	-0,076	0,145	-	-	-	-	-	-
2013	-0,010	0,172	-	-	-	-	-	-
2014	-0,056	0,172	-	-	-	-	-	-
2015	-0,173	0,129	-	-	-	-	-	-
2016	-0,035	0,145	-	-	-	-	-	-
2017	-0,281	0,129**	-	-	-0,263	0,106**	-0,234	0,111*
2018	-0,150	0,129	-	-	-	-	-	-
2019	-0,023	0,129	-	-	-	-	-	-
Intercept	0,366	0,061***	0,347	0,356	0,570	0,308*	0,092	0,361
R-squared	0,278		0,081		0,395		0,312	
F-stat.	0,907		0,920		3,489***		1,726	
No. of obs.	58		58		58		49	

Note: */**/*** denotes statistical significance at the 10/5/1 percent level.

It is of interest to point out that the historical statistics show that mergers were less prevalent during the Dot-Com boom compared to recent years. Back then start-ups, mainly chose to go public in order to break into the industry, raise capital, and grow. In recent years, however, M&A is prefered to IPOs (Statiata, 2019). Nonetheless, FinTech companies' merger deals follow a similar pattern (KPMG, 2018).

Because of the aforementioned reasons, our sample consists of only a fraction of Dot-Com companies that were acquired during the burst of Dot-Com bubble and after, whilst the Fintech sample is set from 2009. Hence, in contrast to the underpricing analysis done in the part preceding this section of the thesis, a clear comparison of the level of cumulative abnormal return of FinTechs firms during their "boom" of these firms and Dot-Com companies during the bubble period cannot be done.

However, the remaining part of the Dot-Com sample consist of deals that were announced during the 6th merger wave whilst Fintech companies are experiencing a surge in the number of deals as well. So, all in all, the comparison still stands to some degree because both the sample of interest and the control group are set in times of similar market conditions.

The first model shows results from the linear regression for the whole sample regarding only time effects. The probability of the F-statistics cannot be rejected, which shows that the overall regression is not the best fit for the sample. Following that, conclusive comments about time effects cannot be made. However, the reason behind this outcome can be because of the low degrees of freedom left, as there are 17 dummy variables and only 58 observations. Nonetheless, once we disregard that, we make use of the significant year-dummies for further variable testing in model 3 and 4.

Next in table 9, the outcome of the second model is shown. This model, which consists of only deal and firm specific characteristic variables as explanatory variables, has a high marginal level of F-test, meaning that the F-test is not significant. Therefore, we cannot say anything regarding the effect that such variables have on the level of 5 day CAR.

Model 3 is where we control for time effects. As it appears in the table, the main independent variable of interest, FinTech, is significant at 5 percent level. As expected, FinTech target companies experience positive abnormal returns around the announcement date of merger.

The other two variables that show to be significant even at a higher significance level, are 2000 and 2017. Because of the limited overlap between the two samples of companies, the “reference” firm is a Dot-Com company acquired in any year except 2000. The intercept is positive, implying that the reference’s CAR is positive as well. The coefficient on 2000 shows that firms acquired in this year, that is Dot-Com companies only, gave higher CARs. As noted previously, because of the lack of overlap between the two samples, the Fintech and 2017 dummy variables represent these firms exclusively. Consequently, the sign of the FinTech shows that FinTech firms acquired in any year except 2017 gave higher CAR than the reference companies, but still lower than the Dot-Coms of 2000, as the lower coefficient implies. Finally, the remaining FinTech companies, namely those that were acquired in 2017 gave a CAR which is on average 0,155-0,263 =-0,108, that is lower than the reference.

In addition, the dummy 2000 representing the year with the most merger announcements for Dot-Com companies is significant as well. There is evidence for high M&A during 2000 is presented in the statistics of M&A between 1985-2018 for software and telecommunications industries, which mostly consist of internet companies (IMAA, n.d.). The variable has the highest coefficient in regression after the intercept and it is significant at five percent level. This implies that the level of abnormal returns to target at merger announcement were affected from the overall market conditions surrounding that period, which is in line with the theory about the correlation between market valuations and merger waves (Rhodes-Kropf & Viswanathan, 2004). The only other year dummy that appears to be significant is 2017, which involves deals of FinTech only. Evidence on 2017 shows even higher growth in M&A activity of FinTechs compared to previous years (KPMG, 2019). The regression outcome can suggest that market mis evaluations might as well have been the driver behind FinTech increased M&A activity.

Other determinants of CAR such as method of payment, industry relatedness, leverage and market capitalization are included as well.

The 5-day CAR shows a statistically significant negative relationship with equity financed deals. As suggested by Jensen (1986) and confirmed by Huang and Walkling (1987), purchases done by equity on average perform worse than cash financed ones.

Alexandridis et al (2012), suggest that investors might be skeptical about the possibility of realizing synergies, considering the difficulties of acquiring large companies. However, we cannot make any inference regarding the proxy for target size, that is market capitalization, as it shows to be insignificant. Similarly, results for the dummy variable of industry relatedness and leverage show insignificant coefficients.

In model 4, the results of the regression with the additional explanatory variable representing deal financial advisor to target are shown. Further interpretation cannot be made as the regression probability of F- statistics is very high.

Additionally, in Appendix 1, the result of a regression containing all the independent and control variables altogether is presented. The probability of F-statistic is higher than 10%, thus showing that the overall model fails to explain anything. Accordingly, we conclude that this specification cannot be used to comment any further. We believe that, again, the low degrees of freedom after including so many variables is what makes this model not significant.

6. Conclusion & Limitations

Using two different methods, this study compares the FinTech and Dot-Com companies with the assumption that they might be valued similarly. The assumption is based by drawing a parallel between historical evidence on highly overvalued Dot-Com companies and current market perception of FinTechs. Accordingly, underpricing level of IPOs and abnormal returns at merger announcement are used as indicators of potential overvaluation.

To conduct the test, we use a total sample of 292 companies, 234 of which belong to IPO transactions during the period of 1995-2019 and 58 M&A deals done between year 2000-2019.

Our research demonstrates that, for the valuation of the companies using IPOs underpricing approach, the level of underpricing of IPOs for these two types of industries is significantly higher during the period of the internet bubble. Thus suggesting large valuation difference between the two is present.

Regarding the M&A transactions, results are mixed. Univariate tests suggest that there seems to be no difference of valuation between these two types of companies. However, results from further testing point towards a similar output as tests of underpricing suggest.

The overall tendency of the outcome of this research is that in the market, these two industries are not perceived as similarly as assumed.

Limitations

The data was obtained from various sources so there might be inconsistency, despite the regular checks. Lack of enough observations for the M&A tests may have also limited the research regarding reliability of results. For further study, we would suggest to include private FinTech companies in the sample for the M&A tests, as well.

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Appendix

Appendix 1. Dependant variable: Cumulative abnormal return

Included observations: 58

Variable	Coefficient	Std. Error	t-Statistic	Prob.
FINTECH	-0.440545	0.130682	-3.371120	0.0018
METHOD	-0.218281	0.083023	-2.629151	0.0125
INDUSTRY	0.027651	0.071437	0.387062	0.7010
LIAB_ASSET	-0.146843	0.114293	-1.284791	0.2071
LN_MKT	-0.035687	0.022868	-1.560594	0.1274
Y_2001	-0.428518	0.135898	-3.153240	0.0033
Y_2002	-0.305753	0.217279	-1.407194	0.1679
Y_2003	-0.137840	0.220813	-0.624237	0.5364
Y_2004	-0.338514	0.117212	-2.888040	0.0065
Y_2005	-0.488537	0.225425	-2.167185	0.0369
Y_2006	-0.311707	0.163214	-1.909810	0.0642
Y_2007	-0.402670	0.162316	-2.480776	0.0179
Y_2009	0.262374	0.240804	1.089579	0.2831
Y_2010	0.201501	0.198037	1.017491	0.3157
Y_2012	0.404864	0.168265	2.406101	0.0214
Y_2013	0.215776	0.180341	1.196490	0.2393
Y_2014	0.285299	0.186243	1.531864	0.1343
Y_2015	0.248932	0.151463	1.643520	0.1090
Y_2016	0.289400	0.159799	1.811024	0.0785
Y_2018	0.170274	0.149132	1.141772	0.2611
Y_2019	0.439746	0.165550	2.656280	0.0117
C	1.267584	0.466672	2.716221	0.0101

R-squared	0.478236	Mean dependent var	0.246419
Adjusted R-squared	0.173874	S.D. dependent var	0.224728
S.E. of regression	0.204259	Akaike info criterion	-0.057160
Sum squared resid	1.501981	Schwarz criterion	0.724387
Log likelihood	23.65764	Hannan-Quinn criter.	0.247268
F-statistic	1.571273	Durbin-Watson stat	1.786408
Prob(F-statistic)	0.113938		

Appendix 2. Pairwise correlation matrix of independent variables in the IPO's sample

	UNDERPRICING	US	AGE	LN_MKTCAP	FINTECH	LN_EXP	REPUTATION
UNDERPRICING	1,000000000	0,181730693	-0,318912354	0,418242219	-0,720402660	0,175058324	0,139049883
US	0,181730693	1,000000000	0,032274364	0,294253805	-0,287711722	0,634405932	0,227038363
AGE	-0,318912354	0,032274364	1,000000000	0,029084252	0,333696142	-0,067591777	0,031235360
LN_MKTCAP	0,418242219	0,294253805	0,029084252	1,000000000	-0,326466493	0,143628345	0,390031219
FINTECH	-0,720402660	-0,287711722	0,333696142	-0,326466493	1,000000000	-0,229284464	-0,096128993
LN_EXP	0,175058324	0,634405932	-0,067591777	0,143628345	-0,229284464	1,000000000	0,230923043
REPUTATION	0,139049883	0,227038363	0,031235360	0,390031219	-0,096128993	0,230923043	1,000000000

Appendix 3. Pairwise correlation matrix of independent variables in the M&A's sample

	CAR	FINTECH	METHOD	INDUSTRY	LN_MKT	LIAB_ASSET	ADVISOR
CAR	1,000000	-0,121015	-0,176751	-0,165112	-0,009666	0,119617	0,090370
FINTECH	-0,121015	1,000000	-0,460566	0,251976	0,011996	0,063101	0,347524
METHOD	-0,176751	-0,460566	1,000000	0,290129	0,066140	0,030486	-0,160058
INDUSTRY	-0,165112	0,251976	0,290129	1,000000	-0,129024	0,100898	-0,131352
LN_MKT	-0,009666	0,011996	0,066140	-0,129024	1,000000	-0,170935	0,457688
LIAB_ASSET	0,119617	0,063101	0,030486	0,100898	-0,170935	1,000000	-0,156835
ADVISOR	0,090370	0,347524	-0,160058	-0,131352	0,457688	-0,156835	1,000000