ERASMUS UNIVERSITY ROTTERDAM

Erasmus School of Economics

The impact of Covid-19 on the initial public offerings of technology companies in North America and Europe

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Bachelor Thesis Economie en Bedrijfseconomie

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Date: 23-08-2021

Abstract

This bachelor thesis examines the impact of the Covid-19 pandemic on the short-term IPO performance of technology firms between 2010 and 2021 by comparing 240 North American and 95 European tech company initial public offerings. Covid-19 has a significant positive relationship with the level of underpricing in both regions; however, Covid-19 has a higher influence in the North American IPO market for technology companies. Furthermore, a firm's age and the proceeds sold during an initial public offering have a negative effect on the level of underpricing, and firms with a bigger market capitalization are more prone to underpricing.

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1. Introduction

On December 31, 2019, China notified the WHO for the first time a cluster of cases of uncommon pneumonia. This pneumonia is identified as a new coronavirus named the SARS-CoV-2 virus (WHO, 2021). Covid-19, a highly contagious and lethal disease, is caused by the SARS-CoV-2 virus. The virus quickly infected and killed millions of individuals across the world, prompting the WHO to classify Covid-19 as a pandemic.

With the start of the pandemic, countries began to close their borders, stock markets began to crash, businesses went bankrupt, people needed to stay at home, and now nearly 200 million cases of covid are reported worldwide, with nearly 4,3 million deaths reported between the first case of Covid-19 in December 2019 and the hand-in of this thesis in August 2021. (WHO, 2021).

However, despite the news of closing borders and crashing stock markets, the Initial Public Offering (IPO) market is flourishing. Baker Mckenzie (2020) reports that in the years of the Covid-19 pandemic the highest global IPO activity is being measured in over a decade. They report that in North America alone, 130 billion dollars of capital is raised across 411 listings in 2020, and over 260 billion dollars of capital is raised through IPO activity in the first half of 2021 (Baker, Mckenzie, 2021).

Furthermore, despite the 2020 market crash and the economic impact of the coronavirus, the level of IPO underpricing of tech companies is increasing throughout the pandemic (Mackintosh, 2021). Companies like DoorDash and Airbnb saw their shares close at 85 percent and 112 percent over their initial offer price on the first trading day, respectively, causing them to leave a lot of money on the table (Levy, 2020). Additionally, four of the 10 largest IPOs in 2020 were technology companies. For example, tech firms such as Snowflake, Airbnb, and DoorDash have collectively funded more than 10 billion dollars (Yahoo Finance, 2021).

Since the Covid-19 pandemic is an extraordinary period for a variety of reasons, the goal of this thesis is to find a solution to the following research question:

What is the impact of the Covid-19 pandemic on the short-term IPO performance of North American and European tech companies?

To answer this main question several sub-questions come to mind. These questions relate to the impact of Covid-19 on several factors which determine the short-term IPO

performance of tech companies. The sub-questions are listed in the theoretic framework.

Because tech firms are frequently underpriced compared to other firms, and the IPO market is flourishing during the pandemic, it is interesting to examine the impact of the Covid-19 pandemic on the short-term IPO performance of tech businesses (Loughran & Ritter, 2004). It is also interesting to investigate if there is a difference in the initial returns of technology firms between North America and Europe during the pandemic since there is little research on this combination of events. Furthermore, it is also interesting to see if the pre-Covid-19 studies and findings on the short-term IPO performance apply during a pandemic, given that there is no research on this yet.

This thesis is organized as follows. Section 2 first discusses the thesis' theoretical framework, which includes an explanation of the short-term IPO anomaly, past research findings, and states the hypotheses. Section 3 subsequently continues to describe the dataset and descriptive statistics. Section 4 explains the methodology used in this research, and Section 5 presents and describes the regression results, from which a conclusion is given in Section 6. Section 6 also discusses the thesis's limitations and recommendations.

2. Theoretical Framework

The preceding literature on the short-term IPO anomaly, also known as underpricing, is discussed in this chapter of the thesis. In this part theories, empirical data, and explanations for the IPO underpricing puzzle are described, and numerous hypotheses are composed as a result.

2.1 The IPO underpricing anomaly

Every day, private companies go public in order to raise capital all around the world. An Initial Public Offering, or IPO, is when a company goes public for the first time. Because IPOs are prone to the anomaly of underpricing, extensive research is performed in the literature on the short-term IPO performance. Underpricing occurs when an IPO is not priced correctly, resulting in a first day closing price that is greater than the initial offer price. As a result, companies that go public 'leave money on the table' (Perera, 2015). Despite the numerous researches, there is still no clear solution to the IPO underpricing puzzle.

2.2 The existence of the IPO underpricing anomaly

To go public, a firm undergoes a costly process with many restrictions and regulations. However, the benefits of raising capital through an IPO exceed the disadvantages of the IPO process, and companies are willing to go public as a result. When a company goes public, an underwriter establishes the IPO offer price and date, and the public can purchase shares. However, with this process, it is frequently the case that the shares are not priced correctly, resulting in more demand and, as a result, the anomaly underpricing.

Ibbotson (1975) is one of the first to discover empirical evidence for the short-term IPO underpricing phenomenon. He sheds light on the underpricing puzzle by examining the IPO performance of freshly issued common stocks from 1960 to 1969. Ibbotson argues in his study that newly issued securities are underpriced by 11,4 percent, and he describes many possibilities that can explain this underpricing. However, because each scenario is subject to irrational behavior, unknown legal constraints, or sophisticated indirect compensation schemes, Ibbotson is unable to draw definitive conclusions about the IPO underpricing problem.

Further, Ibbotson et al. (1994) found empirical evidence that during the time period 1960-1992 the average initial return of 10.626 IPOs was 15,26 percent on US markets.

From 1960 to 1992 was the average initial return per decade was 21,25, 8,95, 15,18 and 10,85 percent respectively. Additionally, Loughran and Ritter (2004) report that the average first-day returns changes over time. From 1980 to 2003 6391 IPOs took place with an average initial return of 18,7 percent. However, during the Dotcom bubble the authors found an average first-day return of 65 percent, but this reverted quickly to an average of 11,7 percent after the bubble burst. From 2001 to 2020 Ritter (2021) reports that the average initial return is 16,7 percent. In this time period 2258 IPOs took place where of 723 IPOs are tech companies.

Since the first researchers discovered evidence for the short-term IPO underpricing anomaly, many researchers have demonstrated that the short-term underpricing anomaly occurs not only in the United States (US), but in countries all over the world. Loughran, Ritter, and Rydqvist (1994), for example, examined data from 25 nations throughout the world and discovered that IPOs in all of the countries studied, are subjected to the underpricing anomaly. For example, the average initial return in Malaysia was 83,3 percent between 1980 and 1991, while the average initial return in the Netherlands was 7,2 percent between 1982 and 1991.

2.3 Explanations of the IPO underpricing anomaly

Asymmetric information

Winner's curse

As demonstrated in the preceding section, numerous researchers found empirical evidence indicating that the IPO market is subjected to the underpricing anomaly. Rock (1986) developed an asymmetric information model to explain the IPO underpricing dilemma. In this model, Rock assumes there are two types of IPO investors: informed investors and uninformed investors. The informed investor is defined as one who has all of the information and will only invest when the issue price is lower than the fair value in order to benefit. Uninformed investors, on the other hand, lack knowledge and are prone to the Winner's curse. The Winner's Curse is the phenomena in which the winner of an IPO, for example, overpays for an issue (Levis, 1990).

According to Rock, uninformed investors are subjected to adverse selection because if the issues are priced below their value, only informed investors will buy the shares because they have more information. When the shares are overpriced, only uninformed investors will buy the issued shares since informed investors do not want

them. To compensate for this adverse selection and information asymmetry, IPOs are likely to be underpriced in order to attract the uninformed investor. Ibbotson et al. (1994) also conclude that factors such as the Winner's curse and information asymmetry contribute to a positive average initial return.

Ex ante uncertainty

Another method researchers try to explain the underpricing anomaly is by investigating ex ante uncertainty. In the paper ‘An Examination of Mispricing, Returns, and Uncertainty for Initial Public Offerings’ Miller and Reilly (1987) examine the daily return, daily volume and daily bid-ask spreads for IPOs in their first and fourth week after issuing. In their study, they discovered a significant correlation between ex ante uncertainty and the level of underpricing in their sample.

Clarkson and Merkley (1994) also investigated the relationship between ex ante uncertainty and the degree of underpricing of IPOs using Canadian IPO data from 1984 to 1987. Similarly, Miller and Reilly (1987) discovered that the degree of ex ante uncertainty proxies influences the level of underpricing. Because ex ante uncertainty cannot be measured with a single variable, researchers employ a variety of proxies that influence ex ante uncertainty. Ljungqvist (2007) argues in his book that company and offering characteristics like as age, IPO gross proceeds, market size, and whether a firm is high tech are popular proxies used to measure ex ante uncertainty.

Signal theory

The signaling theory is being used by Ibbotson (1975), Welch (1989), Allen and Faulhaber (1989), and Grinblatt and Hwang (1989) to explain the underpricing anomaly. According to this theory, companies underprice their securities to indicate to investors that their company is valuable. They aim to reduce the asymmetry of knowledge between the issuer and the investor using this strategy without providing too much information.

According to Ljungqvist (2007), there are also other signal strategies in order to demonstrate the worth of an organization. For example, by using venture capitalists and renowned underwriters, who put their own reputations at risk.

Investor behavior

Despite the fact that the literature is still in its infancy, some researchers also examined IPO underpricing from a behavioral perspective. According to these findings, irrational investors positively influence the level of underpricing by holding optimistic beliefs and, as a result, bid up the price of the IPO shares leading to a higher first day closing price (Ljungqvist, Nanda and Singh, 2004).

Additionally, researchers also investigated whether issuers are vulnerable to behavioral biases. For example, Loughran and Ritter (2002) investigated the influence of mental accounting on the level of underpricing. According to the authors, even though they are leaving money on the table, issuers are often very pleased with the offering, even if there is a high level of underpricing, because they still gain a lot of money. As a result of this habit, underwriters are more likely to set a lower initial offering price, resulting in increased demand.

Other explanations

In addition to the aforementioned authors, several others have attempted to explain the IPO underpricing anomaly. With his ‘Model of the Demand for Investment Banking Advising and Distribution Services for New Issues,' for example, Baron (1982) attempted to explain the IPO underpricing puzzle. In this model describes Baron the effects of knowledge asymmetry between the issuer and the underwriter on the degree of underpricing.

In order to answer the IPO underpricing puzzle, Bajo and Raimondo (2017) investigated the impact of media coverage on the amount of IPO underpricing. The authors find that the level of underpricing rises as a result of increased positive sentiment, better timing of news coverage, and a better reputation of the news provider. Furthermore, Lundmark et al. (2017) discover that the use of social media has a positive effect on the amount of IPO underpricing. Ljungqvist (2007) also provides institutional and ownership explanations for the IPO underpricing anomaly. These explanations, however, are outside the scope of this thesis.

2.4 Hypotheses

The publications cited above attempted to explain the IPO underpricing puzzle by looking into asymmetric information, behavioral biases, and other factors such as the involvement of the media. Their investigations and findings are used in this research to test several hypotheses in order to find an answer to the research question of this thesis. These are described below.

Covid-19 & tech firms

Since Covid-19 is a new concept in the world, there is still a scarcity of literature on the influence of Covid-19 on short-term IPO performance. One of the first to do research on the impact of Covid-19 on IPO performance are Mazumder and Saha (2021). They discovered that during the coronavirus pandemic, the degree of underpricing in 2020 is 9,3 percent higher than in prior years. However, they also discovered that fear related to Covid-19 has a significant negative relationship with the IPO initial returns.

Furthermore, Lyócsa et al. (2020) investigated the effect of Covid-19-related fear on stock market performance. The authors demonstrated, using Google search volume activity, that the massive market loss during the first period of the pandemic was partly caused by short-term investment fear in the stock market. The authors concluded that fear has a significant predictive power for future stock market uncertainty.

Loughran and Ritter (2004) and Demers and Joos (2007) discovered evidence that IT firms are frequently more underpriced than firms in other sectors, due to a higher level of risk and uncertainty. Tech firms are seen as riskier than non-tech companies since they frequently go public at a younger age and are more difficult to value. Additionally, Clark and Merkley (1994) discovered empirical evidence that tech firms have a higher level of underpricing than non-tech enterprises for Canadian companies that went public between 1984 and 1987. Based on these observations, the following hypothesis is proposed:

Hypothesis 1: There is a positive relationship between the presence of Covid-19 and the level of underpricing for tech companies.

Age of the company

The age of a company is the number of years between its founding date and the date of its initial public offering (IPO), at which the firm issues its shares. Many researchers, including Schenone (2004), discovered that a company's age is negatively correlated with its level of underpricing. Ritter (1991), Hensler et al. (1997) and Loughran and Ritter (2004) found empirical evidence that younger firms are more underpriced than older firms, because younger firms have a higher degree of ex-ante uncertainty. These findings support the following hypothesis:

Hypothesis 2: During the Covid-19 pandemic younger tech firms are more underpriced than older tech firms with an initial public offer.

Market capitalization

Market capitalization is calculated by multiplying the total number of issued and outstanding shares by the share price. Market capitalization, according to Boubaker and Mezhoud (2011), acts as a signaling mechanism to inform investors about the quality of a company. Furthermore, according to Bundoo (2007), firms with a greater market capital have a higher level of underpricing. Bundoo also claims that this agrees with the signal theory. As a result, the hypothesis is as follows:

Hypothesis 3: At an IPO the level of underpricing of a tech firm is positively correlated with the market capitalization of a tech company during the Covid-19 pandemic.

Proceeds

Beatty and Ritter (1986) utilized the number of proceeds as an explanatory variable for the amount of underpricing in their study. They discovered empirical data indicating that smaller offers result in greater average initial returns. Proceeds are also used as a proxy by Ljungqvist and Wilhelm (2003), although they use it to measure ex ante uncertainty. Based on these findings, the following hypothesis is proposed:

Hypothesis 4: The number of proceeds at an IPO is negatively correlated with the degree of underpricing of a tech firm during the corona pandemic

Venture capital

According to Jay Ritter (2021), there is an increasing number of venture-backed technological firms going public since 1980. According to his analysis, the percentage of companies backed by venture capital rises from an average of 47 percent in 1980-1989 to an average of 70 percent in 2001-2020. Furthermore, Ljungqvist and Wilhelm (2003) discovered empirical evidence that the presence of venture capital in a company reduces the level of underpricing.

According to Barry, Muscarella, Peavy III, and Vetsuypens (1990), venture capital-backed IPOs have a reduced amount of underpricing. This is due to the fact that venture capitalists actively monitor the companies in which they invest and are frequently specialized. Furthermore, Megginson and Weiss (1991) show that venture capitalists reduce IPO costs and optimize IPO proceeds, resulting in lower initial returns.

Gompers (1996), on the other hand, discovers that the effect of venture capital on the amount of underpricing is dependent on the age of venture capital firms. He believes that younger venture capital firms take companies public too fast, leading to a rise in underpricing. These findings support the following hypothesis:

Hypothesis 5: During the Covid-19 pandemic the presence of venture capital at an IPO result in a lower level of underpricing of tech companies.

Underwriter reputation

Many studies have been conducted to examine the impact of an underwriter's reputation on the extent of underpricing. Carter and Manaster (1990) found empirical evidence for a negative relationship between an underwriter's reputation and the degree of underpricing. According to the authors, prominent underwriters carry less risk, which leads to less educated investors and lower initial returns. Other researchers, including Allen and Faulhaber (1989), Carter, Dark, and Singh (1998), Beatty and Ritter (1986), and Tinic (1988), claim that a higher underwriter's reputation is associated with reduced short-run underpricing. Resulting from these results the hypothesis is as follows:

Hypothesis 6: The presence of a good underwriter at an IPO reduces the level of underpricing of tech companies during the pandemic.

North American and European markets

There are numerous distinctions between the European and American IPO markets. For example, the age at which companies go public, legislation, the number of IPOs each year, and the types of issuers and investors. But the American IPO market has also a 40-day ‘quiet period' following the IPO and the impact of Covid-19 differs between the two areas (Ritter, 2003). For example, there are more Covid-19 cases and deaths reported. As a result, the following hypothesis is proposed.

Hypothesis 7: The Covid-19 pandemic has a greater impact on the level of underpricing in North American than in European regarding the IPOs of tech companies.

3. Data

The dataset in this research is primarily composed with the use of ThomsonOne. A total of 240 North American and 95 European tech companies with an IPO between 2010 and 2021 are included in the dataset. North America consists of the countries United States and Canada and Europe consist of the countries Czech Republic, Denmark, England, Germany, Finland, France, Italy, Netherlands, Norway, Poland, Spain, and Sweden. There are several phases involved in putting together the dataset.

First, in order to select the correct companies in ThomsonOne, this research use the same definition and Standard Industrial Classification (SIC) codes for technology companies as Ritter (2021) and Loughran and Ritter (2004). Using these SIC codes generated a list of 1017 North American and 889 European tech companies that had an IPO between 2010 and 2021. This time period is chosen because of its economic stability. During this period there was no global economic crisis until the Covid-19 epidemic broke out.

After assembling this list of companies, data for the independent variables is retrieved from ThomsonOne. The independent variables consist of the founding date, issue date, offer price, end of day one closing price, market capitalization, the number of proceeds sold, if a company is venture capital backed and the name of the underwriter(s). Additionally, Google finance is used to acquire missing data of the variables. If data for one of the variables is unavailable, missing or the IPO offer price is below 5 dollars, this firm is removed from the dataset. In addition, double values are also removed from the dataset. Appendices A and B provide an overview of all the companies that went public during the time period in the regions North American and European, respectively.

Next to the retrieved independent variables market capitalization and proceeds sold from ThomsonOne, new variables are created to test the proposed hypotheses stated in the theoretic framework. The dependent variable initial return is built using data from the offer price and the end of day one closing price. This variable reflects whether an IPO is underpriced, overpriced, or accurately priced based on its initial return. The following formula is used to compute the average initial return:

$$Underpricing = \frac{First\ Day\ Closing\ Price - Offer\ Price}{Offer\ Price} * 100\% \quad (1)$$

Additionally, in order to regress the initial returns, four extra independent variables are constructed using the obtained data in ThomsonOne. These are the independent variables age, venture capital backed, underwriter reputation and Covid-19. The independent variable age indicates the number of years between the date of the company's founding date and the date of its IPO, and it is determined using the following formula:

$$Age = IPO\ issue\ date - Founding\ date \quad (2)$$

Further, the independent variable venture capital backed is used to identify whether a company is backed by venture capitalists during the IPO process. This variable is converted into a dummy variable that indicates a yes if the IPO is backed by venture capitalists and a no if it is not. Here no is used as the baseline.

The independent variable underwriter reputation is used to identify the reputation of the underwriter responsible during the IPO process. This variable is transformed into a dummy variable states a good if the responsible underwriter is of good quality and a bad if this is not the case. In order to determine the underwriter reputation Jay Ritter's underwriter database 'IPO Underwriter Reputation Rankings (1980 – 2020)' is utilized (Ritter, 2021). Carter and Manaster (1990) developed a ranking method to determine the quality of an underwriter, and Ritter used this method to determine his database. In Carter and Manaster raking method they assign a value from 1 to a bad underwriter reputation and a 9 to a great underwriter reputation. In this study, underwriters with a number of 8 or above in Ritters database are awarded a good, whereas underwriters with a number less than 8 are rewarded a bad. If there are multiple underwriters for an IPO, the underwriter with the highest rating is chosen to determine the underwriter reputation. Here bad is used as the baseline.

Furthermore, the independent variable Covid-19 is utilized to determine whether a tech firm goes public during the corona pandemic or before the pandemic. This variable is transformed into a dummy variable that asserts a yes if the IPO occurs after March 11, 2020, and a no if the IPO occurs before that date. This date is picked because the WHO classified Covid-19 a pandemic on March 11, 2020 (WHO, 2020). Here, no is used as the baseline.

3.1 Descriptive statistics

General

Table 1 shows the number of IPOs and average initial returns of technology companies in North America and Europe separately. North American technology companies are underpriced by 28 percent on average, whereas European technology companies are underpriced by 10,64 percent on average. During the Covid-19 pandemic, both regions experience the highest average annual initial return. In the years 2020 and 2021, a tech company is underpriced by 48,82 percent in North America and 26,90 percent in Europe.

Furthermore, there is a significant difference in the number of IPOs per year between the two regions. Each year, on average, 20 tech firms go public in North America, whereas only 7,92 tech firms go public in Europe. North America and Europe had the most IPOs in terms of annual numbers in 2013 and 2014, with 38 IPOs in North America and 15 IPOs in Europe, respectively.

Furthermore, there is a significant difference between the two regions in terms of the lowest degree of underpricing of technology companies. In 2014, the European region had the lowest average starting return. Europe had an underpricing rating of -1,74 percent in that year, meaning that tech companies were overpriced on average in 2014. In 2010, the lowest average first return in North America was 10,54 percent. In terms of the number of IPOs per year, both areas in the dataset had the lowest number of technology firms going public in 2010.

Table 1: Number of IPOs and average initial return per region per year

(1)	(2)		(3)	
	North America		**Europe**	
Year	Number of IPO's	Average initial return	Number of IPO's	Average initial return
2010	3	10,54%	1	2,49%
2011	8	21,28%	6	11,20%
2012	14	16,86%	6	8,39%
2013	38	21,78%	5	6,18%
2014	27	25,15%	15	-1,74%
2015	25	23,87%	9	7,43%
2016	11	34,66%	5	1,32%
2017	23	19,73%	4	1,71%
2018	13	24,26%	14	6,67%
2019	28	29,64%	6	19,15%

2020	34	48,82%	12	22,67%
2021	16	43,28%	12	26,98%
2010-2021	240	28,00%	95	10,64%

Notes Table 1: Column 1 represents the year an IPO takes place in. A year in this dataset, with the exception of 2021, is from January 1 to December 31. The year 2021is updated till May 26. The number of IPOs and the average initial returns for the areas North America and Europe are reported in columns 2 and 3, respectively. The following countries in Europe have issued an IPO during the period 2010-2021: Czech Republic, Denmark, England, Germany, Finland, France, Italy, Netherlands, Norway, Poland, Spain, and Sweden. The United States and Canada make up the North America region. In each region equal weights are allocated to each IPO to compute the average initial return for the period 2010-2021.

North America

The descriptive data of North American tech enterprises are provided in Table 2. According to the data, during the Covid-19 pandemic, North American tech businesses are on average 17,25 percent more underpriced than before. The initial public offering of the technology firm Code Rebel Corporation is the most underpriced in the region North America, whereas BBTV Holdings Incorporation has the lowest degree of underpricing in this data set.

Furthermore, during the pandemic, technological firms that go public are on average older than they were prior to the emergence of Covid-19. Furthermore, the age gap between the youngest and oldest tech firms that went public expanded by about 32 years during the pandemic.

Another eye-catching statistic is the maximum value of market capitalization of 781206,78 million dollars, or 78 billion dollars at an IPO. This high market capitalization belongs to the tech firm Facebook. As a result of this outlier, the market capitalization average mean rises from 7794,11 million to 11864,70 million dollar. Because it is one of the largest and most impactful technology IPOs in the United States, this outlier is not removed from the dataset.

The final eye-catcher in Table 2 is the 113,77 percent increase in average proceeds sold between the period before and during the pandemic. Furthermore, the high value of maximum proceeds sold prior to Covid-19 is also related to Facebook's IPO.

Regarding the dummy variables, the table reveals that during the pandemic, the number of firms backed by venture capital declines, while the ratio of good to bad underwriters increases.

Table 2: Descriptive statistics of the region North America

	(Before Covid-19)	(During Covid-19)
Underpricing		
Mean	26,82 [32,48]	44,07 [49,65]
Minimum	-27,62	-34,33
Maximum	217,00	201,13
Age		
Mean	10,92 [7,36]	13,75 [14,53]
Minimum	0,15	0,30
Maximum	55,42	87,34
Market capitalization (millions $)		
Mean	11864,70 [57901,90]	7019,79 [13295,89]
Minimum	0,13	51,19
Maximum	781206,78	71828,75
Proceeds sold (millions $)		
Mean	393,89 [1342,77]	842,02 [968,16]
Minimum	5,01	14,38
Maximum	16006,88	4368,15
Venture capital backed		
Yes	126	17
No	64	33
Underwriter reputation		
Good reputation	147	42
Bad reputation	43	8
Number of observations	190	50

Notes Table 2: Column 1 lists the variable names, while columns 2 and 3 outline the statistics before and during the Covid-19 pandemic, respectively. Continuous variables are split out into mean, minimum and maximum and categorical variables are divided into dummy variables. Values and frequencies for continuous and categorical variables are presented in columns 2 and 3, respectively. The standard deviations of the continuous variables are reported in the square brackets. The statistics of the variable Underpricing in columns 2 and 3 are reported in percentages. For the variable Age, the mean, minimum, maximum and standard deviation are reported in years and the variables Market cap and Proceeds sold report their descriptive statistics in millions of dollars in column 2 and 3. Further, the categorical variables Venture capital backed and Underwriter reputation are both divided

into two dummy variables. The variable Venture capital backed is divided into Yes and No which indicates if the IPO is backed by venture capitalist. The variable Underwriter reputation is divided into Good reputation and Bad reputation which indicates the reputation of the underwriter who were involved with the IPO. Column 2 has 190 observations and column 3 has 50 observations.

Europe

Table 3 contains the descriptive statistics of European technology companies. By comparing Tables 2 and 3, it is clear that North America has more tech companies that go public than Europe in this dataset.

During the pandemic, Europe's average level of underpricing of technology firms increases from 5,76 to 25,91 percent. This means that European tech businesses that go public during the pandemic are on average 20,15 percent more underpriced than companies that go public before the pandemic. Compared to the average rise of underpricing in North America this is a difference of 2,9 percent. In Europe, the spread between the lowest and highest levels of underpricing is narrower than in North America. Furthermore, the maximum and minimum levels of underpricing in Europe are less extreme than in North America.

Further, the average age of the firm also stands out. Unlike in North America, the average age of European IT companies that go public during Covid-19 is lower than it was before the pandemic. Also, during the Covid-19 pandemic, the gap between the oldest and youngest tech firms narrowed, whereas it widened in North America. Another eye-catching statistic is the maximum value of 115,52 years for the variable age. This datapoint belongs to the firm Spie, which is a French concern founded in 1900. This data item is likewise not removed because Spie provides services in the fields of energy and communications, which fits Ritters' description of technology enterprises.

During the pandemic the mean value of the variables Market capitalization and Proceeds sold of European tech companies increase significant. The mean variables rise from 3229,75 to 7160,52 dollar and from 288,89 to 502,78 dollar. This is a 121,71 percent increase in the variable market capitalization. The average value of proceeds sold increases by 74,04 percent. In comparison to North America, the average values of both the variables market capitalization and proceeds sold are significantly lower in the periods before and during Covid-19 pandemic. To put this in perspective, the

difference of the average value of the variable proceeds sold between the two time periods is 39,73 percent lower in Europe compared to North America.

The last eye-catching number is that during the pandemic, zero IPOs were backed by venture capitalists, whereas this was 33,33 percent before to the pandemic. This percentage change is nearly the same as in North America, however there are still IPOs backed by venture capitalists in North America.

In Europe, the ratio of good underwriters to bad underwriters decreased by 5,8 percent. In addition, the percentage of good underwriters responsible for the IPO of tech companies prior to and during the pandemic is significantly lower in Europe than in North America.

Table 3: Descriptive statistics of the region Europe

	(Before Covid-19)	**(During Covid-19)**
Underpricing		
Mean	5,76 [11,75]	25,91 [33,54]
Minimum	-16,25	-23,78
Maximum	53,95	141,09
Age		
Mean	17,52 [20,01]	14,24 [12,04]
Minimum	0,10	0,39
Maximum	115,52	50,76
Market capitalization (millions $)		
Mean	3229,75 [6488,49]	7160,52 [8925,78]
Minimum	0,09	44,49
Maximum	35625,00	36812,50
Proceeds sold (millions $)		
Mean	288,89 [512,35]	502,78 [712,22]
Minimum	1,09	2,95
Maximum	2469,04	2655,45
Venture capital backed		
Yes	24	0
No	48	24

Underwriter reputation		
Good reputation	24	9
Bad reputation	48	14
Number of observations	72	23

Notes Table 3: Column 1 lists the variable names, while columns 2 and 3 outline the statistics before and during the Covid-19 pandemic, respectively. Continuous variables are split out into mean, minimum and maximum and categorical variables are divided into dummy variables. Values and frequencies for continuous and categorical variables are presented in columns 2 and 3, respectively. The standard deviations of the continuous variables are reported in the square brackets. The statistics of the variable Underpricing in columns 2 and 3 are reported in percentages. For the variable Age, the mean, minimum, maximum and standard deviation are reported in years and the variables Market cap and Proceeds sold report their descriptive statistics in millions of dollars in column 2 and 3. Further, the categorical variables Venture capital backed and Underwriter reputation are both divided into two dummy variables. The variable Venture capital backed is divided into Yes and No which indicates if the IPO is backed by venture capitalist. The variable Underwriter reputation is divided into Good reputation and Bad reputation which indicates the reputation of the underwriter who were involved with the IPO. Column 2 has 71 observations and column 3 has 24 observations.

3.2 Data adjustments

In the dataset the variables underpricing, age, market capitalization and proceeds sold are winsorized by 5 percent to reduce the impact of outliers in these variables. By winsorizing 5 percent, the top and bottom 2,5 percent are given the value of the datapoints in the 2,5th and 97,5 percentiles, respectively. Further, in order to decrease the right-skewness and normalize the data of the variables, the natural logarithm is also taken from the winsorized variables age, market capitalization, and proceeds sold.

4. Methodology

In order to test the hypotheses and find an answer on the research question, this study uses the following multivariate Ordinary Least Square (OLS) regression model with White's Standard Errors.

$$U_i = \beta_0 + \beta_1 * X_{1i} + \cdots + \beta_j * X_{ji} + \varepsilon_i \quad (1)$$

$U_i = Level\ of\ underpricing\ for\ individual\ company\ i$

$\beta_0 = Regression\ constant$

$\beta_j = Regression\ coefficient\ (j \in \{1, 2, \dots, 6\})$

$X_{ji} = Independent\ variable\ (j \in \{1, 2, \dots, 6\})\ for\ individual\ company\ i$

$\varepsilon_i = Error\ term$

To measure the impact of Covid-19 in North America and Europe individually and North America and Europe combined regressions 2 and 3 are used. Regression 2 consist of three variables representing company characteristics and two dummy variables representing deal characteristics. In regression 3, the third dummy variable Covid-19 is added to the regression.

$$Underpricing = \alpha + \beta_1 * Age + \beta_2 * \ln(Market\ Capitalization) + \beta_3 * \ln(Proceeds) + \beta_4 * D1_{VC\ backed} + \beta_5 * D2_{Underwriter\ reputation} + \varepsilon_t \quad (2)$$

$$Underpricing = \alpha + \beta_1 * Age + \beta_2 * \ln(Market\ Capitalization) + \beta_3 * \ln(Proceeds) + \beta_4 * D1_{VC\ backed} + \beta_5 * D2_{Underwriter\ reputation} + \beta_6 * D3_{Covid-19} + \varepsilon_t \quad (3)$$

5. Results

The regression results are displayed and discussed in this part of the thesis. The regression results of North American tech businesses are displayed and described first. The regression findings of European tech businesses are then reported, followed by the combination of both regions.

5.1 Regression analyses

North America

To regress the initial returns of 240 North American tech companies' IPOs, the natural logarithm of the variables age, market cap, and proceeds, as well as the dummy variables venture capital backed and underwriter reputation, are utilized. The results are shown in Column (1) of Table 4.

According to the regression results of column (1), the variables market cap and venture capital backed are positively significantly related to the level of underpricing by 1 and 10 percent, respectively. In the case of variable market capitalization, a 1 percent increase in variable results in a 0,06 percent increase in the level of underpricing on average. The positive relation of the variable market cap is consistent with the findings of Bundoo (2007) and Boubaker and Mezhoud (2011). The positive association for the variable venture capital backed implies that if a tech firm is backed by venture capitalists and goes public, it would be 7,9 percent more underpriced than if it is not backed by venture capitalists. This measured effect contradicts hypothesis 6.

The age of a tech company, according to model (1), has a negative effect on the level of underpricing. Despite the fact that this discovery is consistent with the current literature, the coefficient is not statistically significant and thus cannot be interpreted. The coefficients of the variables proceeds and underwriter reputation have a positive influence on the amount of underpricing, but these values are likewise not significant and thus can also not be interpreted.

The regression results of the initial return of 240 North American tech company IPOs are also reported in the second column of Table 4. In this regression, however, the dummy variable Covid-19 is also included to the model, which also includes the variables age, market cap, proceeds, venture capital backed, and underwriter reputation.

The variables market cap, venture capital backed, and Covid-19 are all positively significantly related to the level of underpricing by 1 percent, according to the results of the second regression. For the variable market capital, this implies that a 1 percent increase in market capitalization results in a 0,07 percent increase in underpricing on average. The presence of a venture capitalist increases the degree of underpricing by 10,40 percent. The variable Covid-19 has an 18 percent positive effect on the level of underpricing in the model (2). This means that a tech company that goes public during the Covid-19 pandemic will be 18,60 percent more underpriced than a company that goes public before the pandemic.

In model (2), the variable age has an insignificant negative impact on the level of underpricing, as it does in model (1). The variable's coefficient progresses from a positive effect in model (1) to a negative effect in model (2). As a result, drawing conclusions concerning the effect of the variable proceeds sold on the degree of underpricing in publicly traded North American technology companies is difficult. Further, because the variable is also insignificant, interpreting the coefficient is even harder. The dummy variable underwriter reputation is similarly insignificant in model (2) as it is in model 1.

As seen from the F-statistics both models are significant; however, because model (2)'s R-squared is 4,9 percent greater than model (1)'s, model (2) is regarded to be the better model for explaining the variation in the initial returns of North American tech companies. Model (2) also has a smaller root mean squared error (Root MSE), indicating that the data matches model (2) better than model (1).

Further, the two regressions have no multicollinearity problems. To detect multicollinearity between the independent variables in the multiple regression models, Variance Inflation Factor (VIF) tests are conducted. In a multivariate regression model, multicollinearity denotes that there is a strong correlation between two or more independent variables, which reduces the statistical power of the regression model. In this thesis if the VIF-value surpasses the value of 5, there is multicollinearity in the regression. The results of the conducted VIF tests are stated in Appendix 2.

Table 4: Regression results North America

	(1)	**(2)**
Constant	-0.266**	-0.196*
	(0.110)	(0.110)

Ln(Age)	-0.006 (0.019)	-0.010 (0.018)
Ln(Market cap)	0.056*** (0.012)	0.066*** (0.012)
Ln(Proceeds)	0.011 (.023)	-0.029 (0.025)
Venture capital backed		
Yes	0.079* (0.042)	0.104*** (0.039)
Underwriter reputation		
Good	0.018 (0.055)	0.040 (0.055)
Covid-19		
During	-	0.186*** (0.051)
Number of observations	240	240
F-statistic	9,19	11,08
R-squared	0,175	0,224
Root MSE	0,272	0,264

*Notes Table 4: Column (1) reports the estimators of the OLS regression on the results for the level of underpricing for the variables age, market cap, proceeds, venture capital backed and underwriter reputation. The F-statistic, R-squared and Root Mean Squared Error (MSE) are 9,19, 0,175 and 0,272 respectively. Column (2) reports the estimators of the OLS regression on the results for the level of underpricing for the variables age, market cap, proceeds, venture capital backed, underwriter reputation and covid-19. The F-statistic, R-squared and Root MSE are 11,08, 0,224 and 0,264 respectively. Both columns contain 240 observations and the standard errors are reported in squared brackets. The stars reported with the coefficients report the degree of significance. *** is significance at 1 percent, ** is significance at 5 percent and * is significance at 10%.*

Europe

To regress the initial returns of 95 European tech companies' IPOs, the natural logarithm of the variables age, market cap, and proceeds, as well as the dummy variables venture capital backed and underwriter reputation, are utilized. The results are shown in Column (1) of Table 5.

According to the results of the first regression, the variables market cap and venture capital backed are positively significantly related to the level of underpricing by 5 and 1 percent, respectively. In the case of variable market capitalization, a one percent rise results in a 0,03 percent increase in the degree of underpricing on average. In comparison to the North American regression results, a 1 percent change in variable market capital has a 0,04 percent lower influence on the level of underpricing in Europe. In both regressions the coefficients are positive which is in line with the literature. Furthermore, the presence of venture capital at a European IPO of a tech

company results with a 12.6 percent decrease in underpricing. This outcome is consistent with hypothesis 6 in contrast to the results of model (1) of North American companies. Compared to North America, the significance of the coefficient increases in Europe.

The variable proceeds is negatively significantly related to the level of underpricing by 1 percent. This implies that a 1 percent change in the variable proceeds results in a negative effect of 0,05 percent on the level of underpricing.

As with the North American regression results, the regression results of the variable age have an insignificantly negative effect on the amount of underpricing of European tech companies. Furthermore, like in North America, the variable underwriter reputation has an insignificant positive effect on the amount of underpricing of European technology businesses. Because both factors have an insignificant effect, they cannot be interpreted.

The regression results of the initial return of 95 European tech company IPOs are also reported in the second column of Table 5. In this regression, however, the dummy variable Covid-19 is also included to the model, which also includes the variables age, market cap, proceeds, venture capital backed, and underwriter reputation.

According to the results of the second regression, the variables market cap and Covid-19 are positively significantly related to the level of underpricing by 10 and 1 percent, respectively. If the variable market capital increases by 1 percent the level of underpricing increases by 0,02 percent. Furthermore, if a tech firm's IPO occurs during the Covid-19 pandemic, the degree of underpricing increases by 12.9 percent. This is 5,7 percent lower compared to the regression results of North America.

The variable age, proceeds and venture capital backed are negatively significantly related to the amount of underpricing by 10, 1 and 1 percent, respectively. In model (2) the variable age is for the first time significant related to the dependent variable. This implies that when a firm gets older by 1 year the level of underpricing decreases by 0,02 percent. In contrast to model (2) of the regression on North American tech firms, the coefficient of the variable proceeds in Europe is significantly related to the level of underpricing. Furthermore, in Europe, the coefficient does not change from positive in model (1) to negative in model (2). As a result, definitive conclusions about the impact of variable proceeds sold on the degree of underpricing in publicly traded European

technology businesses can be made. In addition, a venture capital-backed IPO will be 9.9 percent less underpriced in model (2). This is a significant contrast when compared to the results of North America, where tech IPOs are more underpriced due to the presence of venture capital.

In model (2) the variable underwriter reputation is the only variable that is insignificant and thus cannot be interpreted.

In both regression models, the constant term in Table 5 has a positive effect on the degree of underpricing. This is a significant difference when compared to the regression models of North American tech businesses, where the constant term is negative in both models. All the models have a significant constant.

According to the F-statistics both models are significant; however, because model (2)'s R-squared is 9,9 percent greater than model (1)'s, model (2) is regarded to be the better model for explaining the variation in the initial returns of European tech companies. Model (2) also has a smaller root mean squared error (Root MSE), indicating that the data matches model (2) better than model (1). Further, the two regressions have no multicollinearity problems as the VIF test values are all below 5. The results of the conducted VIF tests are stated in Appendix 2.

Table 5: Regression results Europe

	(1)	**(2)**
Constant	0,202**	0,196***
	(0,078)	(0,069)
Ln(Age)	-0,020	-0,021*
	(0,013)	(0,012)
Ln(Market cap)	0,026**	0,019*
	(0,010)	(0,010)
Ln(Proceeds)	-0,047***	-0,045***
	(0,016)	(0,014)
Venture capital backed		
Yes	-0,126***	-0,099***
	(0,041)	(0,037)
Underwriter reputation		
Good	0,036	0,048
	(0,042)	(0,038)
Covid-19		
During	-	0,129***
		(0,044)

Number of observations	95	95
F-statistic	5,61	5,77
R-squared	0,262	0,361
Root MSE	0,144	0,135

*Notes Table 5: Column (1) reports the estimators of the OLS regression on the results for the level of underpricing for the variables age, market cap, proceeds, venture capital backed and underwriter reputation. The F-statistic, R-squared and Root Mean Squared Error (MSE) are 5,61, 0,262 and 0,144, respectively. Column (2) reports the estimators of the OLS regression on the results for the level of underpricing for the variables age, market cap, proceeds, venture capital backed, underwriter reputation and covid-19. The F-statistic, R-squared and Root MSE are 5,77, 0,361 and 0,135 respectively. Both columns contain 95 observations and the standard errors are reported in squared brackets. The stars reported with the coefficients report the degree of significance. *** is significance at 1 percent, ** is significance at 5 percent and * is significance at 10%.*

Combined

To regress the initial returns of the North American and European tech companies' IPOs, the natural logarithm of the variables age, market cap, and proceeds, as well as the dummy variables venture capital backed and underwriter reputation, are utilized. The results are shown in Column (1) of Table 6.

According to the results of the first regression, the variables market cap and venture capital backed are positively significantly related to the level of underpricing by 1 percent and 5 percent, respectively. When the findings of the variable market capital model are compared to the results of model (1) in Tables 4 and 5, they are similar. The regression results for the variable venture capital backed are consistent with the results of Table 4's model (1). Both tables show a significant positive relationship between the independent variable venture capital backed and the dependent variable underpricing.

As observed in the regression findings of model (1) in Tables 4 and 5, the regression results of the variable age in model (1) have an insignificant negative effect on the level of underpricing. Furthermore, the effect of the variable proceeds is comparable to the effect of Table 4, because both reflect an insignificant negative relationship with the amount of underpricing in model (1).

In column (1) of Table 6, the coefficient of the variable underwriter reputation positively influences the level of underpricing. However, as seen in Tables 4 and 5, the influence of the variable on the dependent variable underpricing is insignificant and thus uninterpretable.

The regression results of the initial return of the North American and European tech company IPOs are also reported in the second column of Table 6. In this regression, however, the dummy variable Covid-19 is also included to the model, which also

includes the variables age, market cap, proceeds, venture capital backed, and underwriter reputation.

According to the results of the second regression, the variables market cap, venture capital backed, underwriter reputation and Covid-19 are positively significant related to the level of underpricing by 1, 1, 10 and 1 percent, respectively. In contrast to the regression models in Tables 4 and 5, the variable underwriter reputation is significant. According to the findings, the presence of a good underwriter at an IPO increases the level of underpricing of a tech company by 7,6 percent. This effect is in contradiction with the consisting literature. The results for the variable market capitalization are similar to the results of models (2) in the Tables 4 and 5. The results of the variable venture capital backed are consistent with the results of Table 4, and the results of the variable Covid-19 are consistent with the effects of model (2) of the Tables 4 and 5.

In this regression, the variable proceeds sold is the only one that is significantly negatively related to the degree of underpricing. The negative relationship is consistent with the regression results of Tables 4 and 5's second regression models.

In both regression models, the constant term in Table 6 has a negative effect on the degree of underpricing. This corresponds to the regression models used by North American technology companies. However, in Table 6, both constant values are insignificant, whereas in Table 4, this is not the case.

According to the F-statistics both models are significant; however, because model (2)'s R-squared is 6 percent greater than model (1)'s, model (2) is regarded to be the better model for explaining the variation in the initial returns of European tech companies. Model (2) also has a smaller root mean squared error (Root MSE), indicating that the data matches model (2) better than model (1). Further, the two regressions have no multicollinearity problems as the VIF test values are all below 5. The results of the conducted VIF tests are stated in Appendix 2.

Table 6: Regression results North America and Europe combined

	(1)	**(2)**
Constant	-0,102	-0,087
	(0,070)	(0,066)
Ln(Age)	-0,016	-0,018
	(0,012)	(0,011)
Ln(Market cap)	0,053***	0,055***
	(0,009)	(0,008)

Ln(Proceeds)	-0,021 (0,016)	-0,040*** (0,015)
Venture capital backed		
Yes	0,077** (0,032)	0,108*** (0,030)
Good underwriter Reputation		
Good	0,056 (0,041)	0,076* (0,040)
Covid-19		
During	-	0,174*** (0,037)
Number of observations	355	335
F-statistic	15,74	17,93
R-squared	0,180	0,240
Root MSE	0,251	0,242

*Notes Table 6: Column (1) reports the estimators of the OLS regression on the results for the level of underpricing for the variables age, market cap, proceeds, venture capital backed and underwriter reputation. The F-statistic, R-squared and Root Mean Squared Error (MSE) are 15,73, 0,180 and 0,251 respectively. Column (2) reports the estimators of the OLS regression on the results for the level of underpricing for the variables age, market cap, proceeds, venture capital backed, underwriter reputation and covid-19. The F-statistic, R-squared and Root MSE are 17,93, 0,240 and 0,242 respectively. Both columns contain 335 observations and the standard errors are reported in squared brackets. The stars reported with the coefficients report the degree of significance. *** is significance at 1 percent, ** is significance at 5 percent and * is significance at 10%.*

6. Conclusion

This study examines the impact of Covid-19 on the short-term IPO performance of North American and European technology firms before and during the Covid-19 pandemic. This study's research question was:

What is the impact of the Covid-19 pandemic on the short-term IPO performance of North American and European tech companies?

To answer this question, this research uses data of the initial public offering of 240 North American and 95 European tech companies during the period 2010-2021. Using this data, initial return analyses and regressions on the level of underpricing are performed for the two regions. Following the results, Covid-19 has a positive influence on the degree of underpricing for technology companies in the regions North America and Europe going through an initial public offering.

First, the descriptive data in Tables 2 and 3 reveal that during the Covid-19 pandemic, the average amount of underpricing increased significantly in both areas. In North America and Europe, the degree of average underpricing rises by 17.25 percent and 18.93 percent, respectively. Furthermore, the regression findings in Tables 4, 5, and 6 indicate that the dummy variable Covid-19, which indicates whether or not an IPO occurred during the pandemic, has a significant positive relationship with the dependent variable underpricing. Therefore, hypothesis 1: “There is a positive relationship between the presence of Covid-19 and the level of underpricing for tech companies” is accepted.

Despite the fact that certain coefficients are insignificant, the regression findings in Tables 4, 5, and 6 show that the age of a tech firm has a negative relationship with the degree of underpricing. Thus, hypothesis 2: “During the Covid-19 pandemic younger tech firms are more underpriced than older tech firms with an initial public offer” can be accepted. Additionally, hypothesis 3: ‘At an IPO the level of underpricing of a tech firm is positively correlated with the market capitalization of a tech company during the Covid-19 pandemic” can also be accepted, because the regression results show that the variable market capitalization is significantly positively related to the degree of underpricing in all regression models.

Table 4 shows that the ex-ante uncertainty proxy proceeds sold have both a positive and a negative coefficient. These findings, however, are not statistically significant. In

Table 5 and 6 the variable ‘proceeds’ has a significant negative relationship with the degree of underpricing and therefore hypothesis 4: “The number of proceeds at an IPO is negatively correlated with the degree of underpricing of a tech firm during the corona pandemic” can be accepted.

In Tables 4 and 6, the presence of venture capital during a tech company's IPO leads to a rise in underpricing, whereas the presence of venture capital in the area Europe leads to a decrease in underpricing. Because all numbers are meaningful, no clear conclusion can be drawn, and as a result hypothesis 5: “During the Covid-19 pandemic the presence of venture capital at an IPO result in a lower level of underpricing of tech companies.” cannot be accepted for European tech companies. The dummy variable underwriter reputation has a positive effect on the level of underpricing in all regression models. This suggests that the presence of a good underwriter leads to a higher level of underpricing during an IPO. As a result hypothesis 6: “The presence of a good underwriter at an IPO reduces the level of underpricing of tech companies during the pandemic” cannot be accepted.

According to the descriptive statistics of Table 2 and 3 of the IPOs of North American and European tech companies, Covid-19 has a stronger influence on European tech companies than on North American tech companies. In Europe, the average amount of underpricing rises by 1.73 percent more than in North America. Looking at the regression results of Tables 4 and 5, the variable Covid-19 has a stronger effect in the region North America than in Europe. However, in both regions the variable has a significant positive relationship with the dependent variable underpricing. When an IPO occurs during a pandemic, the degree of underpricing increases by 11.8 percent in Europe and 18.6 percent in North America, respectively. Because the variable Covid-19 has a greater effect in North America than in Europe, hypothesis 7: “The Covid-19 pandemic has a greater impact on the amount of underpricing in North America than in Europe related tech company IPOs” can be accepted.

7. Discussion and recommendation

One limitation of this research is that there is only data accessible for the period prior and during the Covid-19 pandemic, as the pandemic is still active at the time this thesis is written. As a result, this study cannot conclude whether Covid-19 has a temporary or lasting impact on the short-term IPO performance of technology companies.

Another limitation of this study is that it only looks at IPOs of North American and European technology companies. Furthermore, because there were limited IPOs during the time period of this study in the pandemic, the sample size of this study is relatively small in contrast to other studies on the short-term IPO performance of tech businesses.

For further research, it would be interesting to examine the short-term IPO performance of tech companies post the Covid-19 pandemic, because this would allow researchers to determine the impact and consequences of the pandemic on the level of underpricing of tech companies. Furthermore, because the pandemic has a different duration and impact in other regions, such as Asia and South America, it is interesting to explore whether the pandemic has a different impact within these regions. Finally, it may be interesting to analyze the impact of the pandemic on various sectors and compare them to the technology industry as Covid-19 to examine if there is a difference.

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9. Appendix

A: North American tech companies in the dataset

A10 Networks Inc	Cloudera Inc	Gogo Inc	MongoDB
Accolade Inc	Cloudflare Inc	GoHealth Inc	Motorsport Gaming Us Llc
ACV Auctions Inc	Code Rebel Corp	GoodRx Holdings Inc	MuleSoft Inc
Adesto Technologies Corp	Commscope Holding Co Inc	GreenSky Inc	NantHealth Inc
Aerohive Networks Inc	Compass Inc	Greenway Medical Tech Inc	Ncino Inc
Affirm Holdings Inc	Contextlogic Inc	GrubHub Inc	New Relic Inc
Agora Inc	Control4 Corp	Halogen Software Inc	NexJ Systems Inc
Airgain Inc	Coupa Software Inc	Health Catalyst Inc	Nimble Storage Inc
Alarm.com Holdings Inc	Covisint Corp	HubSpot Inc	Okta Inc
Allegro MicroSystem Inc	CPI Card Group Inc	Hyrecar Inc	Olo Inc
Altair Engineering Inc	Crowdstrike Holdings Inc	Ibex Ltd	ON24 Inc
Alteryx Inc	Cvent Inc	Ideal Power Inc	One Stop SystemsInc
Ambarella Inc	Cyan Inc	MS & Co Health Holdings Inc	Ooma Inc
Amber Road Inc	Datadog Inc	Imperva Inc	Opower Inc
Amesite Inc	Datto Holding Corp	Imprivata Inc	Pagerduty Inc
Apigee Corp	Demandware Inc	Innova Gaming Group Inc	Paycom Software Inc
AppFolio Inc	DigitalOcean Holdings Inc	Inovalon Holdings Inc	Paylocity Holding Corp
Appian Corp	Docebo Inc	IntelliEPI Inc	Paymentus Holdings Inc
Applied Optoelectronics Inc	DocuSign Inc	Intelsat SA	Phreesia Inc
Apptio Inc	Domo Inc	Intermolecular Inc	Ping Identity Holding Corp
Aquantia Corp	DoorDash Inc	InvenSense Inc	Pinterest Inc
Atlassian Corp Plc	Duck Creek Tech Inc	Jamf Holding Corp	Pivotree Inc
Bandwidth Inc	Dun & Bradst Hldg Inc	JFrog Ltd	Premier Inc
Barracuda Networks Inc	Dye & Durham Ltd	KnowBe4 Inc	Presidio Inc
Baylin Technologies Inc	Dynatrace Inc	Kubient Inc	Procore Technologies Inc
Bbtv Holdings Inc	Elevate Credit Inc	Life360 Inc	PubMatic Inc
Benefitfocus Inc	Endurance Intl Grp Hldg Inc	LifeLock Inc	Pure Storage Inc
Bentley System Inc	Energous Corp	Liquid Holdings Group Inc	Q2 Holdings Inc
BigCommerce Holdings Inc	EPAM Systems Inc	Livongo Health Inc	QTS Realty Trust Inc
Bill.com Holdings Inc	Eventbrite Inc	LMP Automotive Holdings Inc	Qualys Inc
Black Knight Financial Svcs	Everbridge Inc	Lyft Inc	Quantenna Communications Inc
Blackline Inc	Everquote Inc	Marin Software Inc	Rackspace Technology Inc
Blue Apron Holdings Inc	EverSpin Technologies	Marketo Inc	Rally Software Dvlp Corp
Box Inc	Exa Corp	Match Group Inc	Rapid7 Inc
Bumble Inc	ExactTarget Inc	Mavenir Systems Inc	Real Matters Inc
C3.ai Inc	Facebook Inc	MaxLinear Inc	Responsys Inc
Cambium Networks Corp	Fastly Inc	MaxPoint Interactive Inc	RigNet Inc
Cargurus Inc	Figs Inc	McAfee Corp	Ringcentral Inc
Casa System Inc	Fitbit Inc	Medallia Inc	Roblox Corp
Castlight Health Inc	Five9 Inc	MediaAlpha Inc	Rocket Companies Inc
CDW Corp	Flywire Corp	MINDBODY Inc	Ruckus Wireless Inc
Certara Inc	Gigamon Inc	MobileIron Inc	Sabre Corp
ChannelAdvisor Corp	Global Medical REIT Inc	Model N Inc	Sailpoint Tech Hldg Inc
Chegg Inc	GoDaddy Inc	Mogo Finance Technology Inc	Sciplay Corp

SendGrid Inc	Violin Memory Inc
ShiftPixy Inc	Virtu Financial Inc
Shoals Technologies Group Inc	West Corp
Shopify Inc	Workiva Inc
ShotSpotter Inc	Xactly Corp
Signify Health Inc	Xplore Technologies Corp
Silver Spring Networks Inc	Yelp Inc
SiTime Corp	Yext Inc
Smartsheet Inc	Yodlee Inc
Snap Inc	YuMe Inc
Snowflake Inc	Zayo Group Holdings Inc
Sonim Technologies Inc	Zendesk Inc
Sprout Social Inc	Zillow Inc
Summit Semiconductor Inc	Zoom Information Inc
Sumo Logic Inc	Zoom Video Communications Inc
SunEdison Semiconductor Ltd	ZoomInfo Technologies Inc
Sunnova Energy Intl Inc	Zuora Inc
Super League Gaming Inc	Zynga Inc
SVMK Inc	
Switch Inc	
Tableau Software Inc	
Tangoe Inc	
TCP International Holdings Ltd	
Teladoc Inc	
Tenable Holdings Inc	
Textura Corp	
The Trade Desk Inc	
Tradeweb Markets Inc	
Transunion LLC	
Travelport Worldwide Ltd	
Tremor Video Inc	
TrueCar Inc	
Trulia Inc	
Twilio Inc	
Twitter Inc	
Uber Technologies Inc	
UniTek Global Services Inc	
Unity Software Inc	
Upland Software Inc	
Upwork Inc	
Vantiv Inc	
Varonis SysteMms Inc	
Veeva Systems Inc	
Veritone Inc	
Vertex Inc	
Viant Technology Inc	

B: European tech companies in the dataset

Adeunis SA	Median Technologies SA	Wallix Group SA
Adevinta ASA	Mimecast Ltd	Witbe SA
Admicom Oyj	ML SYSTEM SA	Worldline SA
Alkemy SpA	Modelon AB	X-FAB Silicon Foundries SE
Allfunds Group Ltd	Munic SA	Ziggo NV
Altice Sa	NCAB Group AB	
Amalphi AG	Netco Group A/S	
Anevia SA	Network Intl Hldg Plc	
Arcure SA	Nfon AG	
Asetek A/S	Nightingale Health Oyj	
ASK SA	Nordnet AB	
Ateme SA	Norma Group AG	
Atento SA	Numericable Group SA	
AwoX SA	Oceasoft SA	
Better Collective A/S	Officina Stellare SpA	
Ceska Zbrojovka Group Se	Ordissimo SA	
Cint Group AB	Osmozis SA	
Cogelec SA	Ovzon AB	
Coinshares International Ltd	Ozon Holdings PLC	
DNA Oyj	Pexip Holding AS	
DontNod	QIWI PLC	
Edwards Group Ltd	Readly International AB	
Ekinops SA	ReeVo SpA	
Eltel AB	Secure Trust Bank PLC	
FDJ	SFS Group AG	
Fleetmatics Group PLC	Siltronic AG	
Focus Home Interactive SA	Soluciones Cuatroochenta SA	
Frequentis AG	SPIE SA	
GAN Ltd	Stabilus SA	
Globant SA	Sunrise Commun Grp AG	
Groupe ConcoursMania SA	SUSE SA	
Hemnet Group AB	Telefonica Deutschland Holding	
Hensoldt AG	Thunderful Group AB	
Horizontal Software SA	Trifork Holding AG	
Intelligent Energy Hldgs PLC	Tronics Microsystems SA	
Intrasense SA	TUTO4PC.com Group SA	
Kabel Deutschland Holding AG	Unifiedpost Group SA	
Kalray SA	Vantage Towers AG	
KATEK SE	Vercom SA	
Kerlink SA	Vetrya SpA	
King Digital Entertainment PLC	Viadeo SA	
Lime Technologies AB	Visiativ SA	
LINK Mobility Group Hldg ASA	Vogo SA	
Luxoft Holding Inc	Voluntis SA	
Materialise NV	VSG Vange Software Group AG	

C: VIF tests to test for multicollinearity in regression models

North American regression models

```
. vif
```

Variable	VIF	1/VIF
logProceed~2	2.35	0.426019
logMarket_~2	1.93	0.519478
D_Good_rep~n	1.70	0.588558
D_Venture_~d	1.24	0.808827
logagew2	1.07	0.930298
Mean VIF	1.66	

```
. vif
```

Variable	VIF	1/VIF
logProceed~2	2.83	0.353459
logMarket_~2	2.01	0.496957
D_Good_rep~n	1.71	0.584057
D_Yes_Covid	1.33	0.749790
D_Venture_~d	1.27	0.785036
logagew2	1.08	0.927880
Mean VIF	1.71	

European regression models

```
. vif
```

Variable	VIF	1/VIF
logProceed~2	3.43	0.291128
logMarket_~2	2.69	0.372194
D_Good_rep~n	2.00	0.500097
D_Venture_~d	1.48	0.674953
logagew2	1.03	0.966445
Mean VIF	2.13	

```
. vif
```

Variable	VIF	1/VIF
logProceed~2	3.44	0.290781
logMarket_~2	2.76	0.362034
D_Good_rep~n	2.01	0.496789
D_Venture_~d	1.56	0.642048
D_Yes_Covid	1.17	0.854685
logagew2	1.04	0.964784
Mean VIF	2.00	

Combined regression models

```
. vif
```

Variable	VIF	1/VIF
logProceed~2	2.88	0.346627
logMarket_~2	2.15	0.465509
D_Good_rep~n	2.00	0.499961
D_Venture_~d	1.20	0.835758
logagew2	1.04	0.965119
Mean VIF	1.85	

```
. vif
```

Variable	VIF	1/VIF
logProceed~2	3.06	0.327288
logMarket_~2	2.15	0.464696
D_Good_rep~n	2.02	0.494954
D_Venture_~d	1.25	0.797850
D_Yes_Covid	1.18	0.848504
logagew2	1.04	0.964263
Mean VIF	1.78	