Underpricing of European Fintech IPOs

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Date: 28/06/2019

Abstract

This thesis compares the performance of Fintech companies to non-Fintech companies one day after the Initial Public Offering (IPO). This is done with a sample of 2585 European companies, which were listed on a stock market for the first time between 2005 and 2018. To perform this analysis, T-tests and Ordinary Least Squares regression tests were used. The results show that there is no significant difference in underpricing between Fintech and non-Fintech companies.

Keywords: Fintech, Europe, Initial Public Offering, IPO, Underpricing, Linear Regression

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1.0 Introduction

Fintech is a relatively new industry, which in the last decade has shown exponential growth. Often Fintech companies are called disruptive companies (Galvin, et al., 2018). According to the Cambridge Dictionary this means “A new technology that completely changes the way things are done” (Cambridge University Press, 2018). This implicates that these Fintech companies come with great opportunities and expectations but at the same time with lots of uncertainty and risk. Question is to what extend these characteristics of a FinTech company will impact it’s financial performance on the public market.

This thesis will examine the financial performance of Fintech companies one day after the Initial Public Offering (IPO). This IPO is in fact the first time a company offers its shares for public ownership and trading. This process of getting a privately-owned company to offer its shares for the first time is complicated. It involves one or more investment banks to act as so-called underwriters to the IPO. The company going public sells its shares to these underwriters, which than again sells the shares on the offering day to the public. On the first trading day there often is a big increase in price. This increase in price between the offering price and the price after one trading day is called underpricing. There has been a lot of research done about this phenomenon. There are a few different theories about the existence of underpricing, they will be discussed in the next chapter.

There is some research available about Fintech IPOs as well but these studies have mainly focused on IPOs in the United States and China, where also the biggest Fintech IPOs took place. There has been no specific research to date on Fintech IPOs in the EU, while the European market also has a big IPO market including some significant Fintech IPOs. One example of a successful European Fintech IPO is the Dutch based company Adyen. They went public in 2018 and had an offer price of 240 euro. The first trading day these shares were publicly available the price went up with 90 percent to 455 euros, raising the initial valuation of Adyen from 7.1 billion euros to 13.2 billion.

The IPO market is an old market, the first IPO was held in 1602. Interestingly it was the Dutch who had the first IPO in history. In 1602 the Dutch East India company offered its share to the public to raise capital, which made it the first publicly traded company (Goetzmann & Rouwenhorst, 2005). This thesis will solely focus on the European market and the difference we see in IPOs between the Fintech industry and non-Fintech industries. Therefore we get the following research question:

Is there a significant difference in underpricing between Fintech companies and non-Fintech companies with an Initial Public Offerings on the European market?

To analyse this, the database of Thomson Reuters was used. Included in this analysis are all European IPOs from 2005 till 2018. After cleaning the dataset there were 2585 datapoints left. To determine the so-called underpricing we took the difference between the offer price at IPO and the price at the closing of the first day after IPO, divided by the offer price. Ordinary Least Squares (OLS) was used to explain the underpricing with three other dependent variables: Age, DealSize and Private Equity Backed. According to renowned studies of Ritter these variables should have a significant effect (Ritter, 2003). To compare the underpricing of Fintech IPOs with non-Fintech IPOs a dummy was used.

The next chapter will review existing literature about Fintech companies, the underpricing of IPOs and in particular the existing literature about Fintech IPOs. The third chapter is an introduction to the research methodology used, with an introduction of the dataset and the variables. The fourth chapter of this thesis presents the results of the statistical analyses. The thesis ends with a conclusion, which includes a discussion about the limitations and recommendations for further research. Included at the end you will find the references used and an appendix with the full output of all tests.

2.0 Literature Review

This chapter will look at existing literature about the topics discussed in this thesis. Starting with defining what Fintech is and looking at the growth of Fintech in the recent years. Next there will be an introduction on how IPOs work, what underpricing is and why underpricing happens.

2.1 Fintech

In 2016 Schueffel created the following scientific definition of Fintech: “Fintech is a financial industry that applies technology to improve financial activities.” (Schueffel, 2016). This is a broad definition and according to this definition the Fintech industry originated in the sixties in the so-called first stage of Fintech. Arner, Barberis & Buckley introduced the three stages of Fintech. The first Fintech stage started with the introduction of transatlantic telegraph cable, the second stage was marked by the first ATM’s and e-banking. The third and current stage started right after the global financial crisis and is characterized by using technology to remove intermediates, as in using technology to directly offer financial solution to customers (Arner, Barberis, & Buckley, 2017). Most research papers and articles that mention Fintech only refer to Fintech companies from the third stage. This thesis will also only consider companies from this latest Fintech stage. Currently there are more than 12.000 Fintech companies worldwide and this number is vastly growing (Drummer, Jerenz, Siebelt, & Thaten, 2016). Between 2010 and 2016 there has been 50 billion USD invested in Fintech companies (Skan, Dickerson, & Gagliardi, 2016). This number has been increasingly growing and last year in 2018 the total investment in Fintech companies was over 50 billion USD (Mostowyk, 2018).

A lot of these Fintech companies started as a start-up. An example of new Fintech companies are the companies behind cryptocurrencies, these digital currencies based on blockchain technology are speculated to completely change the way people and companies use money. According to Forbes, six of the most innovative Fintech companies are cryptocurrency-related companies (Novack & Schifrin, 2019).

2.2 Initial Public Offering

An Initial Public Offering is the first time a company gets listed on the stock market (Berk & DeMarzo, 2014). This means that at least a part of the company gets public ownership. There are multiple reasons for a company to raise funds through an IPO. Brau, Ryan and DeGraw found out in 2006 that CFOs mainly consider IPOs as vehicles to secure funding for growth and for developing liquidity (Brau, Ryan, & & DeGraw, 2006). One interesting aspect of IPOs is underpricing. This phenomenon of ‘underpricing’ is widely researched over the years. Research has also shown that the average underpricing changed over the years. Between 1990 and 2016 the average level of underpricing shows significant differences. Between 1980 and 1989 the average equally weighted underpricing was 7.2 percent. During the dot-com bubble of 1999 and 2000 it was 64.6 percent (Ritter, 2016). However, in the timeframe of this thesis the underpricing has been fairly stable, except for during the financial crisis (Gandolfi, Regalli, Soana, & Arcuri, 2018). Therefore, in this thesis we won't consider time as an influential factor, but we will take into account the effects of the financial debt crisis. This is done by using a Chow test, which we will elaborate on in the next chapter.

Underpricing is measured as the first day returns, and shown as the percentage change between the offering price of the IPO and the closing price of the first trading day. If the percentage change is positive the shares were underpriced. There are theories that try to explain the underpricing. Ljungqvist found four main theories which will be described in the following paragraph: Asymmetric information, institutional, control and behavioural (Ljungqvist, 2015).

Underpricing Theories

The asymmetric information theory assumes that one party has superior information that others do not have. If one group of investors has superior information over other investors, the better-informed investors only invest in the good IPOs; the underpriced IPOs. Therefore, informed investors will on average get positive returns on the first trading day. The less informed investors will invest in both the good and the bad ones. If there are more bad ones than good ones the less informed investors have no reason to stay in the market. Therefore, the investors will leave the market until the point that there will not be enough investors to participate in all IPOs. In order to keep the less informed investors in the market, their average return should be positive. This can be done by deliberately lowering the offer price and causing underpricing. Thus, the issuer must deliberately underprice the share in order for less informed investors to buy the shares (Rock, 1986). However Ljungqvist also states that firms only care about their own profits and therefore have little reason to underprice their shares so that less informed investors stay in the market creating a free rider problem (Ljungqvist, 2015). Another form of asymmetric information can happen between the investors and the issuing company. Often the issuing company has more information than the investors. The issuing company can choose to underprice their shares as a signal of their quality. Because good quality firms can afford to recover from the loss of money that is left by underpricing their shares. This is an incentive for companies to underprice their shares as it leaves a favourable view of the company and that can be beneficial for the future seasoned offerings (Jindal & Singla, 2016).

Secondly there are three institutional theories for underpricing (Ljungqvist, 2015). The first is the *lawsuit avoidance hypothesis.* This comes from Logue who found out that issuers deliberately underprice their shares to avoid lawsuits from investors who are disappointed with the post-IPO performance (Logue, 1973). The second is *price stabilization*, intended to reduce price drops after the IPO. And the third reason is *tax benefits*, which states that depending on the tax regulations there might be financial benefit to lower or raise the offer price of the shares in certain situations (Ljungqvist, 2015).

The third theory why underpricing exists is an control conflict. Jensen and Meckling state that if the separation of ownership and control is incomplete, an agency problem between managing and non-managing shareholders can arise (Jensen & Meckling, 1976). Instead of maximizing the value to all shareholders, managing shareholders might choose to maximize their own benefits, by underpricing the shares in a way that they can entrench managerial control and thus avoid monitoring by large shareholders (Brennan & Franks, 1997).

The last theory that explains underpricing is behavioural theory (Ljungqvist, 2015). Ljungqvist doubts whether the previous theories are enough to explain the severe degree of underpricing in certain cases. Therefore, he believes that there must be some degree of irrational behaviour. If investors behave irrational, they can bid up the price of the shares beyond the true value causing underpricing.

Underpricing of Fintech Companies

Previous research papers have concluded that high-technology firms do have a higher level of underpricing (Cliff & Denis, 2004) (Lowry & Murphy, 2007). High-technology firms are firms that use new complex technology that is applied to both the final product as well as the production process. A condition is that these products and production processes must be dynamic, meaning they must be continually evolving (Steenhuis & De Bruijn, 2006). While high-technology firms are not equal to Fintech firms they do share certain characteristics. Both often start as a start-up, use new technologies that change the market, and hold possible risk regarding future regulations (Dion, 2019). Dion analysed the underpricing of Fintech firms in North America, in which he compared Fintech firms with nine other industries. He concluded that there is no significant difference between the underpricing of Fintech firms and companies in other industries. Another paper compared the North-American Fintech companies with European Fintech companies. This paper concluded that North-American Fintech companies are significantly more underpriced than European Fintech firms (Steenbergen, 2017). In this paper we will be comparing Fintech firms with non-Fintech firms in Europe. While Dion did not find a significant higher level of underpricing for Fintech firms in North America, Lowry and Murphy did find a higher degree of underpricing for high-technology firms. Therefore, it would be interesting to see if there is a difference in Europe and if there thus is a significant difference in underpricing. Another indication that there might be underpricing for Fintech firms is related to the behavioural theory mentioned before. Looking at Google Analytics, the number of searches for the term ‘Fintech’, has clearly been increasingly growing. Carney stated that the term Fintech is in the first stage of the Gartner Hype Cycle (Linden & Fenn, 2003), meaning the hype is increasingly growing (Carney, 2017). He also stated that the media citations went “through the roof”. And since research has shown that there is a relation between a higher underpricing for firms with higher media interest (Ho, Taher, Lee, & Fargher, 2001), this might indicate higher underpricing for Fintech firms than non-Fintech firms.

3.0 Research Data

As mentioned before, this thesis will analyse the possible effect of being a Fintech company on the underpricing of IPOs. For this test various data sources were used. The following paragraphs will explain how the data was retrieved, explain the variables that were retrieved, and list a statistic table with a summary of all the variables.

3.1 Sample Data

The used dataset consists of all European IPOs between 2005 and 2018. The data was collected with the program SDC Platinum. This program uses the Thomson Reuters database and specializes in extracting data for IPOs. In total 4285 companies were found. The variables that were extracted are: Date Founded, Issue Date, Issuer, SIC code, Bookrunner, Proceed amount, Private Equity Backed, Market Value Before Offer in Dollar, Offer Price in Dollar, Stock Price 1 Day After Offer in Dollar. Even though this thesis focusses on Europe in which the functioning currency normally is the Euro, SDC Platinum is American software and there was more data available in Dollars than Euro's. Therefore, the choice has been made to use the Dollar as functioning currency.

It is not possible to filter for Fintech companies in SDC platinum. Therefore, other databases had to be used. One of the sources used is Financial Technology Partners. They publish a yearly report about Fintech IPOs. This report is mainly focused on the US but there were still 41 European Fintech IPOs mentioned (Partners, 2018). Another database that was used is the CrunchBase database, in which an additional twenty Fintech companies with IPO in the respective timeframe were found. This added up to a total of 61 European Fintech IPOs in the given timeframe of 2005-2018. Unfortunately, SDC Platinum is known for its missing data and its documented errors, so corrections had to be made. These corrections were done using the guidelines of *Online Appendix: Extraction and Cleaning of IPO data from SDC Platinum* (Lowry, Michaely, & Volkova, 2017). After these corrections and deleting the companies with missing data there were 2585 companies with an IPO remaining. And from the identified 61 Fintech companies with an IPO, 41 of these Fintech companies remained.

3.2 Variables Used

Underpricing

As dependent variables the underpricing was used. As explained in preceding chapter, the underpricing is the difference between the offer price and trading price of the first day. The dataset used showed some large outliers. To solve this the data was winsorized with a one-point percentage, meaning the top and bottom one percent of the data set gets deleted and replaced with the first following value after the one-point percent. This greatly improved the significance of the regression.

Log_Age

This is the first independent variable that was used in the regression. It is the difference between the founding date of the company and the issue date of the IPO. Ritter already proved in 1991 that the company's age has a negative relation with the uncertainty involved in the IPO, which follows the logical reasoning that the longer a company exists the more information is available about the company's performance and growth possibilities (Ritter, 1991). This means that on average an older company would have a lower underpricing, newer studies have confirmed that the finding of Ritter in 1991 still hold up today (Loughran & Ritter, 2004). Because the companies age has diminishing effect on the underpricing, the logarithm was taken of the age.

Log_DealSize

Another variable that has a negative correlation with the underpricing is the deal size. This also follows from previous studies (Loughran & Ritter, 2004). As deal size the variable Proceed Amount is used, which could directly be extracted from the Thomson Reuter database. A larger amount of Proceeds is less risky than a smaller amount. And because of the diminishing effect, the logarithm was taken.

Log_MarketCap

The next variable is the MarketCap. This is the valuation of the company before the IPO offering. Schenone states that underpricing is negatively correlated with firm size (Schenone, 2004). To measure the firm size, the Market Value Before Offer was used. This could be extracted using SDC Platinum. Unfortunately, only 1164 companies had a market valuation before the IPO listed in the Thomson Reuter database. This greatly lowered the observations, especially looking at the Fintech effects because only nineteen Fintech companies were included in the 1164 with a market valuation before the IPO.

PrivateEquityBacked

Another independent variable that is used is the dummy PrivateEquityBacked, this is a yes or no variable that is extracted using SDC Platinum. Previous research has shown that having private-equity-backed IPOs have a lower degree of underpricing than non-private-equity-backed IPOs. (Levis, 2011)

Fintech

The independent variable where this thesis is based on is of course the Fintech dummy. This dummy is either one or zero, Fintech or not-Fintech. As mentioned, these Fintech companies had to be handpicked, comparing the dataset with data from Financial Technology Partners and CrunchBase.

Rank_Underwriter

Another possible control variable is the underwriter's reputation. If the reputation of the underwriter is good than there usually is less risk and thus less underpricing involved. The reputation of underwriters itself is not something that can be easily measured. However, there are rankings of underwriters constructed, of which Ritter Underwriter Ranking is the most well-known. Unfortunately, this database is mostly focused on American underwriters, so many of the European underwriters are not included, making it not possible to use the ranking in this thesis. There is however also a European underwriter Ranking (Migliorati & Vismara, 2014) available. However, the problem with this ranking is that the names used for the underwriters do not match the names that are extracted from the Thomson Reuters database. Therefore, it wasn't possible to use the effect of the underwriter's reputation in this analysis.

VARIABLES	Obs	Mean	Sd.	Min	Max	Skewness	Kurtosis
Log_Age	2,589	1.803	0.990	0	3.892	-0.430	2.274
Log_Dealsize	3,021	3.513	2.372	-6.908	9.213	-0.902	4.844
Log_MarketCap	1,317	4.211	2.187	-2.303	11.88	-0.0560	3.384
Winsored1day	3,024	0.113	0.297	-0.374	2.149	2.464	14.45

Table 1. This table shows the summary statistics for the variables used in this Thesis, except for the dummy variables "Fintech" and "PrivateEquityBacked".

3.3 Hypotheses Formulas

To analyse whether there is a significant difference between Fintech and non-Fintech, several tests were used. The first test was a T-test, to test if there is a significant difference in the mean. The second test performed was an Ordinary Least Squares (OLS) regression. OLS is a statistical method for estimating the effects of independent variables on a dependent variable using a linear regression model. The program used to do this OLS test was Stata 14, which has a built-in function to perform this test. Because the variable Log_MarketCap limited the datapoints to 1164 two different models were used. One considering the Log_MarketCap variable and one without, to see if there is a significant difference. The following two formulas were used to test the hypotheses.

$$(1)\ Underpricing = \beta_1 + \beta_2 Log\_Age + \beta_3 Log\_DealSize + \beta_3 Fintech + u_i$$

$$(2)\ Underpricing = \beta_1 + \beta_2 Log_{Age} + \beta_3 Log\_DealSize + \beta_3 MarketCap + \beta_3 Fintech + u_i$$

4.0 Analysis of the Results

In this chapter the different tests and its output will be discussed. Firstly the normality of the variables was tested. Then the Student's T-test and the OLS regression were done to test the hypotheses, followed by several additional tests to verify the results.

4.1 Testing for normality

The initial test that was done is the Shapiro-Wilk test, to analyse if the variables are normally distributed. In Stata the command "*sfrancia*" instead of the standard "*swilk*" was used because the sample size is bigger than 2000. The null hypothesis for this test is that the variables tested are normally distributed. Doing the test gives a P-value of 0.00001 for all variables, meaning we reject the null hypothesis, thus the variables are not normally distributed. Normality is one of the assumptions of the T-test, nevertheless the T-test was still executed, because the T-test is robust to the violation of normality as long as the variables are independent (Edgell & Noon, 1984). The lack of normality fortunately doesn't matter for the OLS regression, as the sample size is sufficiently large and therefore the linear regression is valid (Lumley, Diehr, Emerson, & Chen, 2002). The full output can be found in appendix A.

4.2 T-Test

The first test on the hypotheses that was done was the Student's T-test, to test the difference in mean level of underpricing. The average underpricing for non-Fintech companies was found to be 0,11 and for Fintech companies 0,14. The average underpricing is thus 0,03 percent higher for Fintech companies. However, this difference was not statistically significant, because the T-value was lower than the T-critical. The full output can be found in appendix B.

4.3 OLS Regression

For the second test, as mentioned in the previous chapter, two models were used in the OLS regression. The results of the regressions are shown below in Table 2. The first thing that stands out is that in both models the F-statistic is zero. Meaning the model is highly significant. The R-squared is only 0.021 for the first model and 0.033 for the second, which is not very high, meaning it is not accurate in predicting. However, in this case, it is still economically relevant, because it means that in the first model at least two percent of the underpricing can be explained. This information can be used to only invest in companies that according to this model should have a high underpricing.

Comparing both regressions, it clearly shows that Log_MarketCap has a significant effect and it also improves the R-squared, which would make it a better model. However as said before, using Log_MarketCap greatly reduces the amount of observations.

Looking more closely at the data, we see a confirmation of previous quoted research in a way that Log_Age, Log_DealSize, Log_MarketCap have a negative effect on the degree of underpricing and therefore lowering the underpricing. Because of the logarithm a one percentage increase in the variable translates to a one beta level increase in the underpricing. The PrivateEquityBacked dummy has a positive effect when including the Log_MarketCap and a negative effect when the Log_MarketCap is left out. However, in both cases the F-statistic is higher than the critical value, meaning we cannot draw any direct conclusions from this. As for the Fintech dummy, in both models it showed a positive but non-significant effect.

As can be seen in Table 4, both regressions are done using Robust Standard Errors. This is because there was a significant effect of heteroskedasticity in both linear regression models. This was concluded after doing the White Test in Stata. Both regression models had a Chi-Square value of over 55 which is higher than the critical value, therefore homoscedastic was rejected. The tests and outputs can be found in appendix C.

VARIABLES	(1) Winsored underpricing	(2) Winsored underpricing
Log_Age	-0.00524	-0.0170
	(0.00571)	(0.0104)
Log_DealSize	-0.0173***	-0.00134
	(0.00306)	(0.00466)
Fintech	0.0495	0.0269
	(0.0403)	(0.0385)
PrivateEquityBacked	-0.00136	0.0135
	(0.0194)	(0.0342)
Log_MarketCap		-0.0238***
		(0.00645)
Constant	0.178***	0.255***
	(0.0171)	(0.0364)
Observations	2,585	1,164
R-squared	0.022	0.034

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Table 2. OLS Regression output of the underpricing for both model 1 and 2

4.4 Structural stability

Another test that was done was the Chow test, which tests whether two linear regressions are equal (Chow, 1960). In this case the test was used to see if there is a significant difference before and after the financial crisis. To perform this test the dataset was split using a dummy variable that is zero if the IPO was held before 2011 and one if it was after January 2011. The F-statistic for the Chow test is defined:

$$F(k, n-2k) = \frac{(RSS_P - RSS_A - RSS_B)/(k)}{(RSS_A + RSS_B)/(N_1 + N_2 - 2k)}$$

With the H_0: There is no significant difference between the subsamples. And the H_a: There is significant difference between the subsamples. The test was done for both regression models. Working out for model one and two gives:

$$(1)\ F(4{,}2580) = \frac{(213.67 - 105.92 - 107.21)/4}{(105.92 + 107.21)/(2585 - 2 * 4)} = 1.63$$

$$(2)\ F(5{,}1164) = \frac{(107.48 - 42.26 - 63.71)/5}{(42.26 + 63.71)/(1164 - 2 * 5)} = 3.28$$

The critical F-value at the 5% level significance for model one gives 2,38 and for model two 2,22. This means that for model one we do not reject the null hypothesis, meaning there is no difference before and after the financial crisis. For the second model we do reject the null hypothesis and accept the alternative hypothesis which says that there is a difference between the subsamples. This means that the sample should be divided in a regression model before and after the financial crisis. However, doing this limits the amount of observations drastically. In the period before the financial crisis there are only 406 companies left, of which only four are a Fintech company, making it not statistically relevant. Therefore, we drop model two and take model one as the preferred regression model.

With one preferred regression model left, the next step is to test for multicollinearity. This to make sure the model is valid. Testing for multicollinearity has been done with Stata, using the "*estat vif*" command. This resulted in a mean VIF of 1.01, with the highest VIF value to be 1.02. Having a VIF value of 4 or lower means it is generally accepted to proof there is no significant multicollinearity (Shevlin & Shevlin, 2001). Thus, in our preferred regression model, there is no multicollinearity. The full output can be found in the appendix D.

5.0 Conclusion

This thesis analysed the underpricing of Fintech IPOs in comparison to non-Fintech IPOs in Europe. This was done using a sample of 2585 European IPOs of which 41 were a Fintech company. The first test performed was a T-test, which showed no significant difference in the average degree of underpricing. The second test was an OLS regression test to analyse whether being a Fintech company would influence the underpricing. For this test two different models were constructed, with one of them including the possible effect of company size using the variable Log_MarketCap. But after testing the effect of the financial crisis, using the Chow test, one model was rejected because of limited observations. Therefore, the preferred regression model used Age, Deal Size, Private Equity Backed, and Fintech as the dependent variables. For the variables Age and DealSize the logarithm was taken. The independent variable, Underpricing, was winsorized to deal with outliners. The final results of this OLS regression test show again no significant influence of being a Fintech company on the level of underpricing, which is consistent with similar studies in North America. The results are also consistent with existing studies that showed that DealSize has a significant effect on the underpricing, if the proceeds of the IPO are higher the underpricing is lower.

There were several limitations encountered during the compiling of this paper. Due to choosing the European market, the underwriter’s reputation couldn’t be used as an independent variable. Besides that, the Thomson Reuters database didn’t have all the information on all companies. Therefore, many observations were lost, especially when including the market value of a company before the IPO.

With Fintech being a relatively new but rapidly growing industry, it would be interesting to do this analysis again in a few years from now to see if there would be a significant difference. Another interesting research topic would be a long-term analysis of the financial performance of Fintech companies following an IPO.

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Appendix

Appendix A: Testing for normality

H_0: *The sample is normally distributed*

H_a: *The sample is not normally distributed*

```
. sfrancia Winsored1day Log_Age Log_Dealsize Log_MarketCap
```

Shapiro-Francia W' test for normal data

Variable	Obs	W'	V'	z	Prob>z
Winsored1day	2,981	0.78434	390.528	14.645	0.00001
Log_Age	2,554	0.95448	71.509	10.379	0.00001
Log_Dealsize	2,977	0.95409	83.034	10.844	0.00001
Log_Market~p	1,296	0.99535	3.933	3.191	0.00071

Appendix B: T-Test

H_0: *The sample mean of subsample 0 is equal to the sample mean of subsample 1*

H_a: *The sample means are not equal*

```
. ttest Winsored1day, by(Fintech)
```

Two-sample t test with equal variances

Group	Obs	Mean	Std. Err.	Std. Dev.	[95% Conf.	Interval]
0	2,979	.1122704	.0054543	.2976976	.1015758	.122965
1	45	.1432255	.0374802	.2514248	.0676891	.2187619
combined	3,024	.112731	.0054018	.2970501	.1021394	.1233226
diff		-.0309551	.0446186		-.1184411	.0565308

```
    diff = mean(0) - mean(1)                                      t =  -0.6938
Ho: diff = 0                                     degrees of freedom =     3022

    Ha: diff < 0                 Ha: diff != 0                 Ha: diff > 0
 Pr(T < t) = 0.2439         Pr(|T| > |t|) = 0.4879          Pr(T > t) = 0.7561
```

Appendix C: Testing for homoscedasticity

H_0: *There is homoscedasticity*

H_a: *Unrestricted heteroscedasticity*

```
. estat imtest, white

White's test for Ho: homoskedasticity
         against Ha: unrestricted heteroskedasticity

         chi2(12)      =     55.38
         Prob > chi2   =    0.0000

Cameron & Trivedi's decomposition of IM-test
```

Source	chi2	df	p
Heteroskedasticity	55.38	12	0.0000
Skewness	78.15	4	0.0000
Kurtosis	37.33	1	0.0000
Total	170.85	17	0.0000

Appendix D: Testing for multicollinearity

```
. estat vif
```

Variable	VIF	1/VIF
Log_Dealsize	1.02	0.983645
Log_Age	1.02	0.984979
Fintech	1.00	0.997048
PrivateEqu~d	1.00	0.998679
Mean VIF	1.01	

Appendix E: Full OLS output for model one and two

```
. regress Winsored1day Log_Age Log_Dealsize Fintech PrivateEquityBacked, robust

Linear regression                               Number of obs     =      2,585
                                                F(4, 2580)        =       9.18
                                                Prob > F          =     0.0000
                                                R-squared         =     0.0216
                                                Root MSE          =     .28778
```

Winsored1day	Coef.	Robust Std. Err.	t	P>|t|	[95% Conf.	Interval]
Log_Age	-.0052383	.0057071	-0.92	0.359	-.0164293	.0059527
Log_Dealsize	-.0173423	.0030598	-5.67	0.000	-.0233421	-.0113424
Fintech	.0494853	.0403324	1.23	0.220	-.0296019	.1285726
PrivateEquityBacked	-.0013588	.0194041	-0.07	0.944	-.039408	.0366903
_cons	.1778138	.0170972	10.40	0.000	.1442881	.2113395

```
. regress Winsored1day Log_Age Log_Dealsize Log_MarketCap Fintech PrivateEquityBacked, robust

Linear regression                               Number of obs     =      1,164
                                                F(5, 1158)        =       4.70
                                                Prob > F          =     0.0003
                                                R-squared         =     0.0337
                                                Root MSE          =     .30467
```

Winsored1day	Coef.	Robust Std. Err.	t	P>|t|	[95% Conf.	Interval]
Log_Age	-.0169718	.0104431	-1.63	0.104	-.0374612	.0035177
Log_Dealsize	-.0013426	.0046598	-0.29	0.773	-.0104853	.0078001
Log_MarketCap	-.0238072	.0064451	-3.69	0.000	-.0364526	-.0111619
Fintech	.0268879	.038465	0.70	0.485	-.048581	.1023567
PrivateEquityBacked	.013475	.0341558	0.39	0.693	-.0535392	.0804892
_cons	.2551199	.0364489	7.00	0.000	.1836066	.3266333