Exploring the Influence of Investor Sentiment on IPO Underpricing of Technology Companies

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ABSTRACT

The phenomenon of IPO underpricing is researched since at least the 1960s, with a multitude of possible explanations offered by academia. This study focuses on investor sentiment as a possible determinant for the underpricing of IPOs, focusing exclusively on technology firms. Using the Baker-Wurgler investor sentiment index, a sample of 245 US technology firm IPOs from the period between 2010–2018 is analysed. Through t-tests, a statistically significant difference is found between the average amount of IPO underpricing, depending on the prevalent investor sentiment environment at the time of the IPO. In periods of positive investor sentiment, the amount of underpricing is higher compared to periods of negative investor sentiment. Multiple linear regression models suggest a statistically significant relationship between investor sentiment and IPO underpricing, while controlling for the factors firm age, number of employees, and total transaction value. This study reaffirms earlier studies confirming a relation of investor sentiment and IPO underpricing, offers a new approach to the issue by using the Baker-Wurgler sentiment index, and provides a basis for future research.

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Keywords
IPO underpricing, investor sentiment, technology companies

1. INTRODUCTION

Firms need capital to finance their business operations. Obtaining capital through “going public” – selling parts of a private firm to public investors for the first time (initial public offering, or IPO) – and thereby converting a formerly private into a public firm, regularly generates attention in the business world. Through accessing public equity markets, firms may lower financing costs of their operations. Existing early-stage shareholders can realize their returns from providing capital to the firm by selling their shares to the public. Consequently, a much larger group of people get the opportunity to invest and become shareholders of the firm. Potential drawbacks of becoming a publicly traded firm are the increased scrutiny by regulators and higher demands with regards to financial disclosures. Also, instead of being only accountable to a limited number of providers of capital, after going public a firm needs to answer to a much larger group of shareholders. Lastly, a publicly traded firm is directly exposed to market forces.

The phenomenon of underpricing of IPOs has been confirmed and analysed since at least the 1960s (Reilly & Hatfield, 1969; Logue, 1973; Ibbotson, 1975, p. 146) and empirically researched and detected globally (Loughran, Ritter, & Rydqvist, 1994). IPO underpricing describes stock price gains of new issues on the first day of trading. Underpricing is an immediate economic loss to the issuer. It seems counterintuitive to assume that existing shareholders waive their potentially higher returns deliberately when “going public”. Researchers have conceived a wide range of potential explanations for this “underpricing puzzle” (Ruud, 1993, p. 135).

The average amount of underpricing tends to vary widely over time: Loughran and Ritter (2004) describe average first-day returns of 8% during the 1980s, 15% during 1990–1998, and 65% for the years 1999–2000. These variations may suggest a connection between amount of underpricing and changing investor sentiment regarding the stock market (Ljungqvist, Nanda, & Singh, 2006). Baker and Wurgler (2007) provide evidence that investor sentiment significantly affects stock prices. Focus on investor sentiment as topic of research has recently increased in practice and research (Coqueret, 2020), not least because of the constant advancements in information technology and communication technology lead to a steady growth of potential sources of data for further analysis.

Another reason for widely varying amounts of underpricing described by Loughran and Ritter (2004) is illustrated anecdotally by Baker and Wurgler (2006) that recognize certain themes in stock markets: Depending on the prevailing circumstances, different types of companies are in high demand. In the late 1990s, especially technology companies and its subset of internet-related firms dominated the IPO market in the US (Ofek & Richardson, 2003). These technology companies’ IPOs led to a relative overvaluation or “irrational exuberance” of large parts of the US stock market (Schiller, 2015). Since the bust of the “Dot-Com mania”, some of the then nascent firms have become dominant and well-established factors within the global economy. As of September 2020, seven of the ten largest companies in the world in terms of market capitalization are considered technology companies.[1] Still, even today technology companies’ IPOs are often surrounded by hype and yield extraordinary results: The shares of the online used car seller Vroom returned 118% on its first trading day. Last year, the shared workspace provider WeWork announced its IPO and gave a company valuation of $47 billion, only to significantly reduce it multiple times to around $20 billion, and finally delay it indefinitely. These examples show that technology companies’ IPOs still can lead to extraordinary hype from investors.

This thesis project provides explanations for underpricing by investigating the potentially contributing factor of investor sentiment, focusing especially on IPOs of technology companies. The research question of this thesis is

> *“Does investor sentiment have a relation with IPO underpricing of technology companies in the United States?”*

The analysis is conducted using a dataset spanning from 2010 until the end of 2018, collected from EDGAR (Electronic Data Gathering, Analysis, and Retrieval), the electronic filing system of the United States Securities and Exchange Commission (SEC), as well as the databases Orbis and S&P Capital IQ. Multivariate analysis as well as t-tests will be conducted.

The t-tests establish that under some circumstances, the amount of IPO underpricing is higher in positive investor sentiment periods compared to negative investor sentiment periods. The multiple linear regression shows a statistically significant positive relationship between investor sentiment and IPO underpricing is detected. The model’s control variables firm age, number of employees at time of IPO, and total transaction value are not statistically significant for IPO underpricing. The regression model contributes to explain changes in IPO underpricing.

This study contributes to already existing academic literature confirming a statistically significant relation between investor sentiment and IPO underpricing (Cook, Kieschnick, & Van Ness, 2006; Ljungqvist et al., 2006; Dorn, 2009), but in a previously unstudied time frame. It takes a new approach to the issue by using the Baker-Wurgler sentiment index as measure for investor sentiment. The relation between investor sentiment and IPO underpricing is found to be stronger in negative sentiment periods, an effect not described in former studies.

For practitioners, this study finds that the Baker-Wurgler sentiment index alone is not suitable to predict IPO underpricing. Although the effect is significant, the strength of the relationship does not warrant investment decisions based on this single factor.

Section 2 gives a brief literature review over academically identified causes of IPO underpricing with a focus on investor sentiment and its measurement, as well as the unique characteristics of technology companies. Section 3 contains the thesis’ hypothesis. Section 4 gives an overview over the data collection and screening process, the descriptive characteristics of the dataset, the methodology and data analyses employed in this thesis. Section 5 describes findings and results. The following Section 6 provides a conclusion to the study and states limitations as well as advice for further research.

2. LITERATURE REVIEW

2.1 Explanations for IPO underpricing

2.1.1 Introduction

The underpricing of IPOs has been studied by academia for decades. Multiple explanations and theories to describe IPO underpricing exist. These can generally be classified into four categories (Ljungqvist, 2007): Institutional theories, control theories, asymmetric information theories, and behavioural theories. In the context of this thesis, the focus lies on asymmetric information theories as well as behavioural theories.

[1] Apple, Microsoft, Amazon, Alphabet, Facebook, Alibaba Group, Tencent

2.1.2 Asymmetric information theories

Allen and Faulhaber (1989) describe a signalling effect underpricing can have to investors. Good companies can expect to compensate losses arising due to underpricing, bad companies however cannot use underpricing to signal their alleged quality to investors. A lower price leads to a potentially higher amount of underpricing and thus to a stronger signal.

Akerlof (1970) describes the phenomenon of adverse selection in markets with the existence of information asymmetry between buyers and sellers through the example of the used car markets. Used cars have properties that are known to the seller, but difficult to assess for a prospective buyer. Even a technically skilled buyer must trust the seller about the quality of the used car. Without any further input, the buyer has to expect to be presented with an average quality car and consequently the buyer will only be willing to pay an average price. Sellers of high-quality cars however will be unwilling to put their cars on the market for average prices. This dynamic leads to a continuous quality degradation of all cars offered on the used car market. The described market dynamics are also true with regards to IPOs, where an informed seller wants to sell shares to an informationally disadvantaged prospective buyer.

2.1.3 Behavioural theories

2.1.3.1 Cascades through sequential sales

As mentioned in the introduction, the amount of underpricing varies widely over time. It is doubtful that these variations can solely be explained by the mentioned theories that exclusively assume rational, non-biased players in their models. Welch (1992) constructs a scenario of sequential sales, where early investors in an IPO influence later investors' beliefs of the offering and thereby determine its course: If the share price increases rapidly after IPO, investors could deduct from this that earlier investors had positive information regarding the offering and thereby be encouraged to invest as well. This may start a self-reinforcing feedback loop or "cascade", as Welch (1992) terms it, driving up the price of shares, as subsequent investors are incentivized to profit as well from the assumed superior knowledge of the earlier investors. Of course, this development has also validity for IPOs with negative price developments early on, where investors are deterred from investing assuming superior knowledge of earlier investors.

Welch's assumptions are empirically demonstrated by Amihud, Hauser, and Kirsh (2003) that notice "cascades" of demand at the Tel Aviv Stock Exchange in both directions, thereby underpricing or overpricing of an IPO. The described effect could be described as investor sentiment, however not investor sentiment regarding the stock market, but more regarding the specific firm's share "cascading" up or down. Investor sentiment regarding the stock market as a whole is described below.

2.1.3.2 Investor sentiment as determinant of IPO underpricing

Ljungqvist et al. (2006) present evidence that the presence of non-rationally acting investors influences underpricing of IPOs. Investor sentiment is stated as reason for the irrational exuberance of certain investors. Cook et al. (2006) describe a statistically significant relationship of investor sentiment – depicted by newspaper articles describing the respective IPO – and the amount of underpricing when the firm goes public.

Through an analysis of German IPOs, Dorn (2009) determines that the sentiment of retail investors has an influence on IPO performance.

Defining investor sentiment

Financial models are often founded on the assumption of exclusively rational acting investors, unaffected by emotions. Shiller established that stock price volatility is "five to thirteen times too high" to be explained exclusively by changes of the fundamental value of the underlying stocks (Shiller, 1981, pp. 433–434). Black (1986) introduces the concept of noise applicable to actors in financial markets. "Noisy traders" do not act based on rational information, but individual, possibly irrational beliefs. Black states that only the presence of these irrational actors "make financial markets possible" (Black, 1986, p. 530). Without sufficient differences in actors' assessments of assets' fundamental values, there is only little incentives to trade and therefore no functional pricing mechanism.

Shiller describes positive investor sentiment as "a feeling that nothing can go wrong" (Shiller, 2000). Baker and Wurgler notice that "classical finance theory leaves no role for investor sentiment" (Baker & Wurgler, 2006, p. 1645) and call it an describe investor sentiment as an "intrinsically elusive concept" that is hard to measure directly. Only indirectly, through proxies, it may be approximated. Zhou (2018) agrees, stating that investor sentiment can only be estimated. Investor sentiment is defined as "the factor that explains why asset prices diverge from their fundamental value" (Coqueret, 2020, p. 2).

Investor sentiment proxies

A wide range of proxies is described in literature as measures of investor sentiment. Zweig (1973) describes the discount of closed-end fund shares as measure to estimate investor sentiment. Charles, Shleifer, and Thaler examine Zweig's claim empirically and conclude that "discounts on closed-end funds are indeed a proxy for changes in individual investor sentiment" (Charles, Shleifer, & Thaler, 1991, p. 107).

Neal and Wheatley (1998) describe closed-end fund share discounts as measures of investor sentiment as long-known "market folklore" but substantiate the proposition by analysing data from 1933–1993.

Whaley (2000) describes the Chicago Board Options Exchange's Volatility index (VIX) as "investor fear gauge". It is a measure of expected future stock market volatility. The higher the index, the greater is the expected volatility. High index levels signal investors' negative sentiment towards the stock market. Through analysing volatility and returns of the S&P 100 index from 1986–2000, Whaley concludes that the VIX is a reliable "barometer of investors' fear of the downside" (Whaley, 2000, p. 17). Simon and Wiggins (2001) confirm the use of the VIX to quantify investor sentiment. Through evaluation of the interplay of future contracts of the S&P 500 and the VIX, they report a "statistically and economically significant predictive power" of the VIX as investor sentiment measure (Simon & Wiggins, 2001, p. 461).

Coqueret (2020) describes the automated extraction of investor sentiment data from newspaper articles, internet sources and even weather data or sport results as potentially viable proxies to quantify investor sentiment.

Baker-Wurgler sentiment index

Baker and Wurgler (2006) reject the existence of one single, directly observable measure representing investor sentiment. To approximate investor sentiment, they construct a composite index to approximate investor sentiment consisting of five (originally six, but see proxy 6 below) underlying proxies suggested by literature:

(1, 2) IPO activity: Shiller (1990) describes IPO markets as subject to temporary "fads", thus sentiment. Both the number of IPOs and their first-day returns are each a proxy in the model.

(3) Closed-end fund discount: As mentioned above, Zweig (1973) and Charles et al. (1991) use the closed-end fund discount as proxy for investor sentiment. In the model it is defined as the average difference between the net asset values of closed-end stock fund shares and their market prices.

(4) Equity issues: Through analysing data from 1928–1997, Baker and Wurgler (2000) propose the share of equity issues in total new equity and debt issues as predictor for stock returns and link it directly to investor sentiment. The ratio of equity issuance and the equity plus long-term debt issuance is added to the model. While at first sight very similar to proxies 2 and 3, this measure also includes seasoned equity offerings and debt financing activity.

(5) Dividend premium: Baker and Wurgler (2004) describe the difference of the average market-to-book ratios of dividend payers and non-payers as proxy for investors' demand for dividend paying stocks. This follows the logic proposed by Fama and French (2001) that dividend paying stocks are generally of established, profitable firms with weaker future growth prospects. Investors may evaluate such stocks as safer, compared to non-payers.

(6) High liquidity or volume: Baker and Stein propose high liquidity "as symptom of the fact that the market is dominated by … irrational investors, and hence is overvalued" (Baker & Stein, 2004, p. 271). The natural logarithm of the turnover ratio of trading volume to the number of shares listed on New York Stock Exchange (NYSE), detrended by the 5-year moving average is the first proxy of the composite index.

However, the turnover ratio as part of the construct has since been removed altogether from the composite index, as according to Wurgler "[t]urnover does not mean what it once did, given the explosion of institutional high-frequency trading and the migration of trading to a variety of venues".[2]

Baker and Wurgler conclude that each of the proxies consists of two parts: One part constitutes the proxies' sentiment component, while the other part is made up of "idiosyncratic, non-sentiment related components" (Baker & Wurgler, 2006, p. 1656). By employing principal components analysis, the proxies' common component is isolated and merged into one measure. Two variants of the index are calculated: One based exclusively on the mentioned proxies (called SENT by Baker and Wurgler), and one corrected to remove influences of larger business cycles (called $SENT^{\perp}$). The $SENT^{\perp}$ index is assessed as the "cleaner prox[y]for investor sentiment" by Baker and Wurgler (2006, p. 1657).

The Baker-Wurgler sentiment index (BW index) is used frequently by researchers to measure investor sentiment (Hribar & McInnis, 2012; Cen, Lu, & Yang, 2013; Huang, Jiang, Tu, & Zhou, 2015; Antoniou, Doukas, & Subrahmanyam, 2016; Chang, Lin, Luo, & Ren, 2019).

Firth, Wang, and Wong (2015) follow the overall approach of the BW index, but add two further proxies to their model to account for the particularities of the underdeveloped nature of the Chinese stock market that is the subject of their study: growth of savings deposits, and growth of investment accounts.

As it is widely used in literature for analysis of mature stock markets, calculated using a broad array of inputs, the BW index ($SENT^{\perp}$ variant) is used in this thesis project as proxy to quantify investor sentiment.

2.2 Technology companies' characteristics

Technology firms have become an important factor in the global economy and a highly investigated object in research (Grinstein & Goldman, 2006). Lowry, Officer, and Schwert (2010) describe technology companies as especially hard to correctly value, as their business models are much more uncertain that business models in more traditional and proven business sectors. Distinct definitions of the term "technology company" remain controversial in literature and vary substantially. Koberg, Sarason, and Rosse describe the endeavour even as "definitional Tower of Babel" (Koberg, Sarason, & Rosse, 1996, p. 16).

Since there has been no generally valid definition and a lack of agreement which companies should be categorized as "technology firms", Grinstein and Goldman conducted an exploratory study and determined characteristics of tech firms, such as high orientation towards research and development activities supported by an appropriate organizational structure (Grinstein & Goldman, 2006). A further distinction between "high-tech", "medium-tech" and "low-tech" can be found in the literature "based on the respective sectors' average share of expenditures for research and development" (Kirner, Kinkel, & Jaeger, 2009, p. 447).

When it comes to technology firms in the context of financial research oftentimes classification systems are used to identify companies with similar operating characteristics to enable comparability of economic firm factors (Bhojraj, Lee, & Oler, 2003). A common system to classify industries for reflecting and analysing economic issues is the US-based Standard Industrial Classification System (SIC), developed by the US Government in the 1930s (Dalziel, 2007). SIC represents "a taxonomy used by the Bureau of the Census to divide firms (enterprises) and their individual manufacturing plants (establishments) into uniform categories that reflect similarities between uses for the products they produce or the manufacturing technologies they employ" (Clarke, 1989, p. 17). Although it was since mostly replaced by the Northern American Industry Classification System (NAICS), it is still used, both in practice and recent research, due to its high availability to classify industries and define technology firms (Brown, Martinsson, & Petersen, 2017; Arora, Belenzon, & Patacconi, 2018; Templeton, Petter, French, Larsen, & Pace, 2019).

Financial studies recommend different sets of SIC codes in order to select and distinguish technology companies (Francis & Schipper, 1999; Loughran & Ritter, 2004; Kile & Phillips, 2009). In this context, Kile and Phillips compared a combination of SIC codes and compared it to a set of NAICS codes with the result that their recommended SIC code set provides the opportunity to generate larger-size samples of technology companies, which leads to a more powerful statistical sampling (Kile & Phillips, 2009). Since technology companies are the focus of this research project, academic literature has been scanned to identify a recommended and already tested set of SIC codes to generate an appropriate selection of technology companies. Loughran defined a set of SIC codes for tech stocks (Loughran & Ritter, 2004), which can be also found, in slightly modified forms, in recent studies (Arora et al., 2018; Templeton et al., 2019).

3. HYPOTHESIS

As stated in the literature review, investor sentiment influences stock returns in general, and the performance of IPOs specifically. This is also emphasized by the fact that a widely used proxy for investor sentiment – the Baker-Wurgler sentiment index – is

[2] http://people.stern.nyu.edu/jwurgler/data/Investor_Sentiment_Data_20190327_POST.xlsx

decisively influenced by IPO activity, as two of its five sub-components are IPO related.

Ljungqvist et al. (2006) find that underpricing of IPOs varies and is especially present in positive investor sentiment environments. Cook et al. (2006) describes the presence of sentiment traders as factor leading to higher underpricing. Dorn (2009) notices that sentiment driven retail investors positively affect underpricing.

Baker and Wurgler (2007) list criteria of stocks especially susceptible to investor sentiment. Stocks of "companies that are younger, smaller, more volatile, unprofitable, non–dividend paying, distressed, or with extreme growth potential (or companies having analogous characteristics)" (Baker & Wurgler, 2007, p. 132). IPOs of technology companies may be especially hard to assess, as the underlying business models of such firms are uncertain and surrounded by hype (Lowry et al., 2010). Loughran and Ritter (2004) determine that IPOs of technology companies are prone to higher amounts of underpricing compared to IPOs of firms in other sectors.

To test if these implications are still valid today, the following hypothesis is stated:

> *Hypothesis – Investor sentiment has a positive relation with IPO underpricing of technology companies in the United States.*

4. DATA & METHODOLOGY

4.1 Data collection

The observation period of this thesis project spans from the beginning of 2010 until the end of 2018. Using S&P Capital IQ, all IPOs in that timeframe are gathered. The analysis only includes IPOs filed with major US stock exchanges (New York Stock Exchange, NASDAQ Global Market, NASDAQ Global Select Market), as these have comprehensive filing requirements and therefore ensure higher data availability. In line with the screening approach of Loughran and Ritter (2004), IPOs of real-estate investment trusts, banks and partnerships, as well as offers with a price below $5 per share are excluded from the sample. The complete screening procedure is depicted in Figure 1 below. By going through this screening procedure, a sample with high quality data availability, consisting of 245 technology company IPOs large enough to be relevant to institutional investors, is achieved.

Period of IPO: 1/1/2010 - 1/12/2018
13399 firms

↓

Stock Exchange: NYSE, NasdaqGM, NasdaqGS
1536 firms

↓

Security Type: Common Stock
1461 firms

↓

Country of Incorporation: United States
1378 firms

↓

Loughran & Ritter (2004) criteria: No REITs, blank check firms, banks
758 firms

↓

Business sector: Technology companies
245 firms

Figure 1: IPO screening logic

To calculate the amount of underpricing of a respective IPO, stock price data is collected from S&P Capital IQ. In cases of incomplete data regarding offer price or closing price, the Orbis database is consulted. A firm's age is derived by calculating the period from a firm's founding date (sourced from EDGAR) to the date of its IPO. The SIC codes used to identify and filter for technology companies, broadly following the definition of "technology company" employed by Loughran and Ritter (2004), Arora et al. (2018) and Templeton et al. (2019) are collected through EDGAR. S&P Capital IQ offers complementing data regarding firms' SIC codes. BW index data is available through Jeffrey Wurgler's website.[3] The number of employees at time of the IPO is sourced from EDGAR. The total transaction value is provided by S&P Capital IQ.

4.2 Empirical model

To test this thesis' hypothesis – Investor sentiment has a positive relation with IPO underpricing of technology companies in the US – the following linear regression model is applied:

$$Underpricing_t = \alpha + \beta_1 (BW)_{t-1} + \beta_2 (\text{Age})_t + \beta_3 (Employees)_t + \beta_4 (TTV)_t + \varepsilon$$

In Table 1, the variables of the models are defined. More detailed descriptions of the variables can be found in section 4.3.

Table 1: Variable definitions

Variable	Definition
Underpricing_t	$\frac{Price_{Close} - Price_{Offer}}{Price_{Offer}} \times 100$
BW_{t-1}	Baker-Wurgler sentiment index, lagging by one month, BW 1 or BW 3 variant
Age_t	$Year\ of\ IPO\ -\ Year\ of\ firm's\ founding$
Employees_t	Number of employees at time of IPO
TTV_t	$Number\ of\ shares\ \times\ offer\ price$

This table gives a brief overview of the variables of the linear regression model.

Next to the main analysis above, an analysis on the positive and negative investor sentiment subsamples is conducted.

4.3 Variable descriptions

Amount of underpricing is the dependent variable in the model. It is defined as the initial percentage return of a share on its first trading day:

$$Initial\ return = \frac{Price_{Close} - Price_{Offer}}{Price_{Offer}} \times 100$$

The Baker-Wurgler sentiment index (BW index) is the independent variable in the model. It is a composite index consisting of five underlying proxies suggested by literature (see Section 2.1.3.2 above) and calculated on a monthly basis. As described in literature, it is seen as a lagging variable. It is expected that the current investor sentiment influences IPOs that take place in the close future. In line with the analysis of Baker and Wurgler (2007), positive investor sentiment periods are defined as above average index values for the observation period, while below average index values depict negative investor sentiment periods.

Two different variants of this variable are used in this study. BW 1 is the value of the BW index ($SENT^{\perp}$ variant). BW 3 is calculated as the average of the previous three BW 1 index values and determined on a rolling basis for each month of the examined period. For BW 1, an IPO taking place in January of 2010 uses the BW index value of December 2009, and for BW 3 the average

[3] http://people.stern.nyu.edu/jwurgler/data/Investor_Sentiment_Data_20190327_POST.xlsx

of the BW index values for October, November, and December of 2009 is used.

Age is a control variable and describes the age of the firm at the time of going public. In this study we will use a proxy because the exact founding dates of firms are not known. As for the IPO the exact day is known, the variable is calculated in full years. Age is derived by calculating the difference from a firm's founding year to the year of its IPO. Ritter (1984) claims that the age of a company is a measure of how established it is. Older companies exhibit a lower amount of uncertainty with regards to its pre-IPO valuation. Ritter (1984) additionally argues that more established companies do not have to leave as much "money on the table" compared to less established companies that may still have to attract investors with lower prices to compensate for their higher valuation uncertainty.

Employees is a control variable and depicts the number of employees at the time of IPO. The rationale of including it in the model largely follows the explanation for the variable Age stated above. More established firms with less valuation uncertainty may on average be companies with higher numbers of employees.

TTV is a control variable and depicts the total transaction value. Total transaction value is defined as the total dollar amount raised on the day of going public, including potential overallotment amounts. It is calculated as follows:

$$Transaction\ value = Number\ of\ shares\ \times\ offer\ price$$

As the variables underpricing, age, employees and TTV are severely skewed and contain many outliers, winsorization is applied at the 5th and 95th percentile.

4.4 Univariate analysis

Table 2 shows the descriptive statistics of the variables of the dataset.

Table 2: Descriptive statistics of variables

Variable	Mean	Median	S. D.	Min.	Max.
Underpricing	23.418	19.230	23.502	-5.844	76.930
BW 1	-0.078	-0.065	0.228	-0.894	0.384
BW 3	-0.817	-0.056	0.226	-0.832	0.325
Age	11.608	10.000	5.639	3.200	25.800
Employees	759.926	514.000	736.792	74	2797
TTV ($mln)	156.388	105.573	135.105	39.055	572.538

This table is based on a sample of technology firm IPOs between 2010-2018 in the United States, collected from S&P Capital IQ, Orbis and EDGAR. BW 1 values are supplied by Jeffrey Wurgler's website, BW 3 is the rolling average of three monthly BW 1 values. The variable definitions can be found in Table 1. All variables are based on 245 observations.

On average, a technology company's IPO shows underpricing of 23.42%, with a minimum first day return of -5.84% and a maximum of 76.93%. The average age of a technology company at time of IPO is 11.61 years. The youngest firm is 3.20 years, the oldest 25.80 years old. The average firm employs 759.93 people at time of the IPO, with a minimum of 74 and a maximum of 2797. The total transaction value is $156.39 million on average, with $39.06 million as minimum and $572.54 million as maximum. The values of BW 1 are on average around -.08 in the observed time frame, with a low of -.89 and a high of .38. BW 3 displays an average of -.08, with a low of -.89 and a high of .32.

5. RESULTS

5.1 Bivariate analysis

As mentioned earlier, the complete sample exhibits an average underpricing of 23.42%. However, depending on investor sentiment at time of the IPO, the average underpricing differs. Independent t-tests are used to investigate if the differences between the subsamples are statistically relevant. Both variables measuring investor sentiment – BW 1 and BW 3 – are analysed. The results can be seen in Table 3.

Panel A of Table 3 shows a comparison of the means and medians of the variables, split by investor sentiment according to BW 1. In positive investor sentiment periods, the average IPO is underpriced by 26.69%, with a median underpricing of 23.92%. In negative investor sentiment periods, IPOs are on average 21.45% underpriced, with a median underpricing of 17.65%. The mean difference is -5,23% and statistically significant at the 10 percent level. The other variables' subsamples do not show a statistically significant difference.

Panel B of Table 3 compares the means and medians of the variables, split by investor sentiment according to BW 3. In positive investor sentiment periods, IPOs are on average 28.04% underpriced, with a median underpricing of 25.42%. In negative investor sentiment periods, the average IPO is underpriced by 20.49%, with a median underpricing of 16.31%. The mean difference amounts to -7.55% and is statistically significant at the 5 percent level.

The mean and median differences for TTV depending on investor sentiment according to BW 3 as displayed in Panel B is high: In positive investor sentiment periods, the average total transaction value of an IPO is 176.12 million US $, with a median of 116.00 million US $. In negative investor sentiment periods, an IPO has an average total transaction value of 143.89 million US $, with a median of 100.00 million US $. This mean difference of -32.23 million US $ is statistically significant at the 10 percent level. When comparing the means and medians of TTV as depicted in Panel A depending on investor sentiment according to BW 1, the difference between the subsamples is smaller and not statistically significant.

Concluding, based on the analysis carried out, the amount of underpricing differs significantly depending on the investor sentiment prevalent at the time a firm goes public. This difference increases when longer periods to gauge investor sentiment – BW 1 as short-term view compared to BW 3 as a medium-term outlook – are considered. The statistical significance of the differences between the means is higher for BW 3 with 0.014 compared to BW 1 with 0.014. A possible explanation for the difference between BW 1 and BW 3 could lie in the construction of the BW composite index. It is provided monthly, but only as of the last day of the month. As such, it is subject to higher variations that get averaged out when calculating an average based on 3 monthly values.

Taking BW 3 as measure of investor sentiment, the total transaction value of IPOs also differs statistically significant between the sentiment sub-samples. One possible explanation for this could be, that larger scale IPOs time the date of going public with a favourable investor sentiment environment.

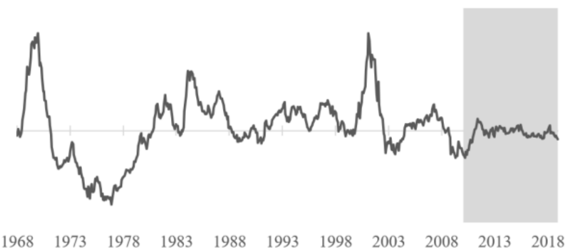

Figure 2: Baker-Wurgler sentiment index (BW 1) from 1968–2018, with examined period highlighted

Table 3: Mean, medians, and t-test statistics of variables, split by investor sentiment periods

Panel A: Comparison of positive and negative investor sentiment periods, according to BW 1							
	Positive		Negative		t-test for Equality of Means		
Variable	**Mean**	**Median**	**Mean**	**Median**	**Mean Difference**	**t-value**	**Sig. (2-tailed)**
Underpricing	26.685	23.915	21.453	17.650	-5,231	-1.694	0.092
BW 1	0.105	0.085	-0.189	-0.100	-0.294	-12.442	0.000
BW 3	0.080	0.089	-0.179	-0.121	-0.259	-10.355	0.000
Age	10.870	10.000	12.052	11.000	1.183	1.595	0.112
Employee	762.467	476.500	758.399	523.000	-4.069	-0.042	0.967
TTV	168.255	105.287	149.252	105.600	-19.002	-1.025	0.307
Panel B: Comparison of positive and negative investor sentiment periods, according to BW 3							
	Positive		Negative		t-test for Equality of Means		
Variable	**Mean**	**Median**	**Mean**	**Median**	**Mean Difference**	**t-value**	**Sig. (2-tailed)**
Underpricing	28.039	25.420	20.491	16.310	-7.547	-2.475	0.014
BW 1	0.086	0.083	-0.183	-0.100	-0.269	-10.940	0.000
BW 3	0.093	0.092	-0.192	-0.121	-0.285	-12.080	0.000
Age	10.989	10.000	12.000	11.000	1.011	1.388	0.167
Employee	794.779	528.000	737.853	492.000	-56.926	-0.587	0.558
TTV	176.121	116.000	143.890	100.000	-32.231	-1.759	0.080

Panel A of this table shows the means, medians, and t-test statistics, split by positive and negative values for investor sentiment based on variable BW 1. It includes 92 observations in positive investor sentiment periods, and 153 observations of negative investor sentiment periods. Panel B shows the means, medians, and t-test statistics, split by positive and negative values for investor sentiment based on variable BW 3. It includes 95 observations in positive investor sentiment periods, and 150 observations of negative investor sentiment periods. The variable definitions can be found in Table 1.

Table 4: Regression results

	Complete sample			***Sub-sample: Positive investor sentiment***		***Sub-sample: Negative investor sentiment***	
	Control	BW 1	BW 3	BW 1	BW 3	BW 1	BW 3
Variable	**Model 1**	**Model 2**	**Model 3**	**Model 4**	**Model 5**	**Model 6**	**Model 7**
BW 1		0.147**		-0.408		0.189**	
		(0.025)		(0.245)		(0.019)	
BW 3			0.148**		-0.566		0.132*
			(0.026)		(0.158)		(0.087)
Age	-0.006**	-0.005*	-0.005*	-0.007	-0.005	-0.004	-0.006*
	(0.046)	(0.063)	(0.069)	(0.209)	(0.379)	(0.176)	(0.071)
Employees	0.000	0.000	0.000	0.000	0.000	0.000	0.000
	(0.310)	(0.315)	(0.300)	(0.142)	(0.204)	(0.718)	(0.718)
TTV	0.000	0.000	0.000	0.000	0.000	0.000	0.000
	(0.132)	(0.206)	(0.206)	(0.119)	(0.273)	(0.577)	(0.392)
Intercept	0.285***	0.297***	0.297***	0.379***	0.386***	0.294***	0.286***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
R Square	0.032	0.052	0.052	0.067	0.056	0.045	0.057
Adj. R Square	0.020	0.036	0.036	0.024	0.003	0.031	0.031
N	245	245	245	92	95	153	150

This table shows 7 linear regression models. Model 1 is a regression of all control variables. Models 2 and 3 are regressions of the whole sample. Model 4 is a regression of a subsample including only IPOs in positive investor sentiment periods, according to BW 1. Model 5 is a regression of a subsample only including IPOs in positive investor sentiment periods, according to BW 2. Model 6 is a regression of a subsample including only IPOs in negative investor sentiment periods, according to BW 1. Model 7 is a regression of a subsample only including IPOs in negative investor sentiment periods, according to BW 3. The variable definitions can be found in Table 1. p-values in parentheses, *p<.1, **p<.05, ***p<0.01

When examining the Baker-Wurgler sentiment index over a longer time frame (see Figure 2), a clear stabilization in the examined period of 2010–2018 is apparent, with a much larger range of the index in the mentioned more volatile periods.

Lower volatility and more uniform investor sentiment data could lead to weaker informative value of the investor sentiment proxy in the examined period.

Table 5: Correlations of variables

	1	2	3	4	5	6
Underpricing (1)	1					
BW 1 (2)	0.160	1				
BW 3 (3)	0.162	0.952	1			
Age (4)	-0.151	-0.066	-0.081	1		
Employees (5)	-0.035	0.075	0.090	0.253	1	
TTV (6)	0.064	0.141	0.154	0.044	0.684	1

This table shows the Pearson correlations of each of the variables. The variable definitions can be found in Table 1

5.2 Multivariate analysis

When examining the Baker-Wurgler sentiment index over a longer time frame (see Figure 2), a clear stabilization in the examined period of 2010–2018 is apparent, with a much larger range of the index in the mentioned more volatile periods.

Lower volatility and more uniform investor sentiment data could lead to weaker informative value of the investor sentiment proxy in the examined period.

Table 5 above shows the Pearson correlation of each of the variables. Apart from the high correlation of both BW 1 and BW 3, it is apparent that multicollinearity is not an issue.[4] Several other tests are performed to ensure that all the necessary assumptions of the multiple linear regression model are fulfilled. After winsorization of Underpricing, Age, Employees and TTV, all variables are normally distributed and extreme outliers eliminated. Through inspecting the normal probability plots of the standardized residuals, as well as the scatter plots of standardized predicted values and standardized residuals, the assumptions of normality, linearity and homoscedasticity are fulfilled.

Table 4 above shows the results of the multiple linear regression models. Model 1 includes all three control variables, Age, Employees and TTV. Age has a statistically significant effect at the 5 percent level, albeit only small with -0.006.

Model 2 uses BW 1 as investor sentiment measure, while Model 3 uses BW 3, and thus the average of the BW index values of the 3-month period before the respective IPO, to measure investor sentiment. Both models return virtually identical results, with only BW 1 or respectively BW 3 showing as statistically significant at the 5 percent level within the model. In both cases, the effect is positive, with 0.147 for BW 1 in Model 2 and 0.148 for BW 3 in Model 3. As in Model 1, Age is statistically significant in both models at the 10 percent level, again with a small coefficient of -0.005.

Model 4 and Model 5 consider only IPOs in positive investor sentiment environments according to BW 1 and BW 3, respectively. None of the two models' variables is statistically significant when only considering these cases.

Model 6 and Model 7 only include IPOs in negative investor sentiment periods according to BW 1 and BW 3, respectively. Both models show a statistically significant effect of investor sentiment on the dependent variable Underpricing. Model 6 shows a statistical significance of investor sentiment at the 5 percent level, with a coefficient of 0.189. The statistical significance of investor sentiment in Model 7 is at the 10 percent level and has a coefficient of 0.132.

A potential reason for this statistical significance in negative investor sentiment periods could be the conclusion of Baker and Wurgler (2007) that assumed higher average monthly returns in lower sentiment periods for speculative and difficult-to-arbitrage stocks.

In none of the seven examined regression models, the variables Employees or TTV are statistically significant.

Evaluating the quality of the examined models, we see low R Squared values. For example, Model 7 has an R Squared value of 0.057. This means only 5.7% of the variance of the dependent variable Underpricing can be explained by the examined regression model. Since this value is low, it can be considered as a poor model fit. Other factors outside of the regression models are influential.

6. CONCLUSION

6.1 Deductions from the performed analyses

This thesis project investigated the relationship of investor sentiment and IPO underpricing. Its research question is

> *"Does investor sentiment have a relation with IPO underpricing of technology companies in the United States?"*

The thesis project's hypothesis is

> *Hypothesis – Investor sentiment has a positive relation with IPO underpricing of technology companies in the United States.*

By employing t-tests, it was found that for technology companies, the amount of underpricing is higher during positive investor sentiment periods compared to negative investor sentiment periods. This difference is statistically more significant when looking at longer investor sentiment periods (3-month period in this case). When looking at shorter periods (1-month period), the effect of higher IPO underpricing on average in positive sentiment periods compared to negative sentiment periods can be observed as well. However, this observation's statistical significance is lower.

Based on the conducted multiple linear regression a statistically significant positive relationship between the Baker-Wurgler sentiment index chosen in this thesis to act as proxy for investor sentiment and the dependent variable IPO underpricing is found. Thereby, the stated hypothesis can be accepted. The models' control variables firm age, number of employees at time of IPO, and total transaction value are not statistically significant for IPO underpricing. The regression model contributes to explain changes in IPO underpricing, as 5.2% of the variance of the dependent variable underpricing can be explained by the examined regression model.

The thesis project's research question can therefore be answered favourably: Investor sentiment has a (positive) relationship with IPO underpricing of technology companies.

The study thereby reaffirms earlier findings by Cook et al. (2006), Ljungqvist et al. (2006), and (Dorn, 2009) that observed a relationship between investor sentiment and amount of underpricing.

[4] VIF scores are low throughout all models and variables, ranging from 1.027 to 2.474.

While previous studies approximate investor sentiment by analysing newspaper articles regarding the IPO (Cook et al., 2006), above average participation by retail (Dorn, 2009) or sentiment (Ljungqvist et al., 2006) investors in the IPO, this study as well found a relation when using the Baker-Wurgler sentiment index as proxy for investor sentiment. The fact that the relationship between investor sentiment and amount of underpricing is significant in negative sentiment periods is previously not described in academic literature.

For the practitioner, this study suggests that investor sentiment is a measurable factor determining IPO underpricing. However, the found effect when using the single examined proxy for investor sentiment is not strong enough to base investment decisions on it alone. A more robust proxy, presumably made up of more inputs to approximate the investor sentiment, should be used.

6.2 Limitations & suggestions for further research

The conducted analysis was limited to the period between the years 2010–2018. During this time, stock prices in the United States generally followed a positive trend. Coming out of the financial crisis and supported by favourable government policies, major stock market indices reached high valuations without any too significant price drops. Consequently, the range of investor sentiment during that period – while not totally flat – was relatively stable compared to more volatile periods, like for example the financial crisis around 2008 or the Dot-Com bubble around 2000. Indeed, as already stated earlier above, examining the long-term development of the Baker-Wurgler sentiment index (see Figure 2 above), a clear stabilization of the index becomes apparent, with a much larger range of the index in the mentioned more volatile periods and before.

Additionally, the Baker-Wurgler sentiment index is calculated monthly. A more regularly recorded proxy may yield higher informative value by capturing the influence of often short-termed shifts in investor sentiment and its influence on market movements and thus also IPO underpricing. Examining longer periods with more shifts in investor sentiment on the one hand and using a proxy for investor sentiment with shorter calculation intervals may lead to more robust results. Also, more factors explaining underpricing should be added to an examination. Valuation metrics, financial ratings and a more accurate industry classification scheme may be relevant. As explained, the term "technology company" is not necessarily specifically definable.

Broader analyses covering all industries could uncover additional effects, especially in business areas with lower uncertainties surrounding its business models.

In general, the thesis presents a basis for further research. Further proxies measuring investor sentiment should be tested for their potential value in explaining IPO underpricing.

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