The Effect of Investor Sentiment on IPO Underpricing

A Comparative Industry Analysis

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Abstract

This paper examines the correlation between IPO underpricing and investor sentiment. IPO underpricing is quantified in the form of the spread between the offer price set by issuers and the price paid by investors at the closing of the first trading day. Investor sentiment is quantified by computing a multitude of proxies, with the focus being on the ARMS-index. Furthermore, this paper compares the aforementioned correlation over different separate industries. The results of the regression tests point to a slight positive correlation (at the 0.1 significance level), found for the ARMS measure as well as for the Put/Call-ratio using options of both equity and indices.

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1 Introduction

During and following the internet-bubble of the late 1990s, academics showed growing interest in the phenomenon of underpricing of initial public offerings (henceforth IPO's). Research showed that, on average, the first day return on the stock of an IPO was an exuberant 18.8% from 1980 to 2001 in the USA (Ritter and Welch 2002). This blatant underpricing of stocks is theorized to have multiple reasons, mostly based on information asymmetries and agency problems (Ljungqvist 2005). Numerous behavioural theories have also endeavoured to explain IPO underpricing by looking at, amongst other aspects, investor sentiment (Ljungqvist, Nanda and Singh 2006).

Next to this, previous research has found a positive correlation between the annual volume of IPO's and the inflation-adjusted level of the stock market (Loughran, Ritter and Rydqvist 1994). This points to the propensity of stock issuers to time their IPO's to gain from positive market conditions, and the investor sentiment that these conditions accommodate.

This paper aims to quantify and explain the effect the level of investor sentiment has on the extent of IPO underpricing. Campbell et al. (2008) conduct similar research by testing for the same correlation between IPO first-day-return with an investor sentiment index constructed by Baker and Wurgler (2006, 2007). The contribution of this paper to existing literature lies in the difference in quantifying investor sentiment and its empirics, also testing for the difference in the effect across industries.

First of all, this paper will review the extensive literature on the theorized reasons for IPO underpricing and proceed to focus on behavioural explanations based on investor sentiment. Investor sentiment can, in general terms, be specified as a belief about future cash flows and investment risks of an asset that is not justified by the facts at hand (Baker and Wurgler 2007). Furthermore, this paper aims to review the theorized incentives issuers have in capitalizing on investor sentiment by timing their IPO's within positive states of the market (Rajan and Servaes 1995).

The empirics of this paper will firstly be built up out of several regressions testing for the relationship between investor sentiment (in the form of the ARMS-index) with IPO underpricing, in the form of first-day-return. The data will include 5,499 different IPO's, spanning form January 1990 to November 2017, which are subdivided over 12 different industries. The regressions will incorporate fixed effects to control for individual differences between each industry and date of issuance. Lastly, substitute variables computing investor sentiment will be incorporated to test the robustness of the model using the ARMS-index as main measure for investor sentiment.

The main research question of this paper is: what is, and what contributes to, the correlation between IPO underpricing and investor sentiment and how can this be witnessed across different industries? Subsequently this paper will try to search for theoretical evidence on how stock issuers are utilising this potential correlation by timing their IPO's in different market settings.

The rest of this paper is organised as follows. Section 2 reviews literature on IPO underpricing, investor sentiment and the timing of IPO's in different market conditions. Section 3 develops the hypothesis while section 4 discusses all used data and methodology. Section 5 presents the empirical findings and, lastly, section 6 summarizes and concludes this paper.

2 Literature Review

2.1 General reasons for IPO underpricing

Ibbotson (1975) was one of the first to provide an extensive number of possible reasons for IPO underpricing, which have been further used by many other academics. As Ritter and Welch (2002) mention in their review of IPO literature, it is highly unlikely that a simple risk premium and/or market misvaluation is the cause of the entire, aforementioned, first-day return of 18.8 % for IPO's. More must be going on and many academics begin their review of the reasons for underpricing of IPO's by looking at the situation of information asymmetry.

Information asymmetry is often linked to the fundamental description mentioned by Akerlof (1970) in his theory on the market for lemons. This description is based on a simple situation in which a buyer does not know the quality of the offered product, while the seller of course does know the full extent of the product's characteristics. This leads to the buyer not wanting to pay more than the price he would be willing to pay for an average product, resulting in the expulsion of products of high quality that require a high price. Linking this to IPO's, within a situation in which the issuer is more informed than the investor, a rational investor will never bid more than the average price and only issuers with worse-than-average quality are willing to sell their shares at the average price (Ritter and Welch 2002). Underpricing originates out of this problem due to the fact that issuers with high quality stocks deliberately set an offer price below their fundamental value, as to deter low quality issuers. This goes together with the hope that this initial sacrifice will be compensated post-IPO, once the stock's quality is better known, through future issuing activity (Welch 1989).

Rock (1986) portrays the related problem in which some investors are informed and others are described as uninformed about the true value of a stock. He imposes the "winners curse" where uninformed investors receive all the shares they bid for in unattractive offerings, due to informed investors not bidding on these prospects. Alongside this, in attractive and under-priced offerings, they are rationed out by the simultaneous bidding of the informed investors. This can lead to uninformed investors receiving an eventual negative return and warrants that issuers should slightly under-price their stock to ensure the continued participation of uninformed investors, as they still can benefit from their capital.

Benveniste and Spindt (1989) contribute with literature on the situation in which issuers have less information than investors on a right offering price. They tie this to the practice of book building in which underwriters, which are investment banks tasked with the actual issuance of the issuing firms stock, try to gain information from investors preferences and bidding potential. Eventual underpricing originates out of this practice, as underwriters often have to offer investors IPO allocations and a lower price in return for this information (Ritter and Welch 2002).

The discretion of allocating the IPO's stock to investors of choice and setting the offering price, appointed to underwriters, leads to principal-agency problems between issuer and underwriter. This due to the fact that underpricing represents the wealth transfer from the issuer towards the investor and this gives stage to rent- seeking behaviour by the underwriter (Ljungqvist 2005). An example of such behaviour is the acceptance of side-payments by underwriters, in the form of high trading commissions for unrelated deals paid by investors for allocations in an IPO's stock (Loughran and Ritter 2002). Next to this, an underwriter can also choose to allocate highly under-priced stocks to certain investors they wish to do further business with, which is called spinning (Ljungqvist 2005).

Overall it seems that IPO underpricing stems mostly from the situation in which there is an asymmetry of information between the issuers and investors in IPO's. This asymmetry leads issuers to offer their stock at a lower price to deter offerings of lower quality and to ensure the participation of lesser informed investors. The next segment will look at investors' behavioural biases and how these can increase the price investors are willing to pay for a stock at IPO.

2.2 Investor sentiment biases

The literature on behavioural explanations for market pricing anomalies has picked up in the past two decades, contradicting the classical assumption of complete rationality in investors. Most of these explanations surround investor sentiment and the behavioural biases that are paired with this. The two biases that seem to tie in best with IPO underpricing are investor overconfidence and the self-attribution bias.

Daniel et al. (1998) define an overconfident investor as one who overestimates the precision of the private information he has gathered next to the public information available to all investors. They found evidence that investors overreact to private signals, leading to sharp stock price fluctuations, and underreact to later public information which leads to a gradual correction of the stock price to a certain full-information value. The authors name these two phases the 'overreaction phase' followed by a 'correction phase'.

Placing this into the context of IPO underpricing, this overreaction phase could lead investors to overestimate their private information on the value of an issued stock and in turn overestimate the value of the stock. This effect would work next to issuers already underpricing the IPO (as can be read in the previous literature section), leading to a larger spread between the price at which a stock is issued and the price investors are willing to pay.

In line with this, Ritter (1991) finds that in the subsequent months after the listing the initial price increase of an IPO seems to evaporate due to under performance of these stocks in comparison with the stocks of matched non-IPO firms. Over a longer period of time it seems that stocks that were initially under-priced at IPO may actually have been overpriced by investors above the fundamental value of the stocks. Aggarwal and Rivoli (1990) come to similar results. They find that the returns of investors who bought an issued stock at the offering price and held it for 250 days were significantly negative on average. Investors that bought the stock for the price at the closing of the first trading day were found to have received an average -13,73% return, after controlling for market movements. This is strong evidence for the argument that investors are subject to over-valuation of issued stocks; Aggarwal and Rivoli (1990) appoint this to certain investor 'fads' in early after-market trading.

The self-attribution bias holds the effect in which the confidence of an investor increases after a positive impulse, and decreases less after a negative impulse. Psychological evidence points to the tendency of investors to credit themselves for success, but blame external factors for failure (Roth 1975). In the context of IPO's, this bias would go hand-in-hand with overconfidence as investors who gain from high first-day returns would be positively stimulated even when their valuation was higher than the fundamental value of the stock. On the other hand, they will be influenced less by the subsequent price rundown of the stock towards the stable fundamental value.

Highlighting these two behavioural biases, Deaves et al. (2010) conduct research on the level of overconfidence of stock market forecasters, using data from a survey which asked respondents for 90% confidence intervals of the German stock index 6 months ahead. The authors first of all find that market forecasters are overconfident. Their results also find that, while overconfidence persists, there is a learning effect as intervals widen following failure and narrow following success in equal measure. The authors conclude that increased market experience is correlated with an increased level of overconfidence, as these investors have attributed much of their success to their own abilities while downplaying their losses.

Overall it seems that due to the inherently biased nature of investors to be overconfident investors might overestimate the value of a stock at IPO. Alongside this, their potential gain in first-day-returns will be attributed to their own knowledge while their failure in overpricing the stock above fundamental value will be self-attributed to a lesser extent. The empirics of this paper will attempt to quantify market sentiment in such a manner that it expresses a level of optimism or pessimism. When these levels are relatively high this paper assumes that there is a larger chance that investors are overconfident in their assumptions.

2.3 Market timing and industry sentiment

Rajan and Servaes (1995) construct a model in which they express the relationship between investor sentiment and feedback trader risk with anomalies consistent in the IPO market. One of these anomalies is the so called 'window of opportunity' in which issuers and underwriters aim to time their IPO's to coincide with market conditions in which investor sentiment is high and feedback risk is small.

Within their model the authors proxy sentiment as the relative market to book ratio of a certain industry. They find that a one standard deviation increase in this relative sentiment increases the number of IPO's from that industry by 31 % the standard deviation. A positive relationship that implies issuers, if they are rational enough to know and actively test for this relationship, would benefit from timing their IPO in a period with high relative sentiment.

Ibbotson and Jaffe (1975) were one of the firsts to academically research the prediction of so-called 'hot-issue' markets. The authors define these as periods in which new issues perform relatively well during the first month after their issuance. Within their data on first-month premia they find a serial correlation that indicates a predictability for hot-issue markets": historic data suggests that hot-issue markets follow after other hot-issue markets.

As mentioned earlier, Loughran, Ritter and Rydqvist (1994) find evidence of a high volume of IPO's near market peaks, in a correlation between the annual volume of IPO's and the inflation-adjusted level of the stock market. The authors appoint this correlation, first of all, to the relatively high stock prices making it increasingly beneficial to raise external equity capital. Looking at all the aforementioned examples, the existing literature thus suggests a predictability of "hot-issue markets" and evidence that issuers are successfully timing their IPO's to coincide with these peaks.

Furthermore, in his theory on the existence of certain windows of opportunity, Myers (1984) mentions how firms are placed into a financing pecking order. He states that asymmetric information drives up information costs to such levels that external equity is only acquired when cash and debt financing are used up. Myers and Majluf (1984) mention that firms aim to reduce their information costs by issueing equity in periods in which information asymmetry is low. Sticking to the setting of asymmetric information, Bayless and Chaplinsky (1996) find that investors react differently to firm and market conditions in hot and cold markets, pointing to greater concern for firm-specific information (and indirectly information asymmetry) in cold markets.

Another interesting aspect is to look at the characteristics of the firms that issue in either a "hot" or "cold" market setting. Previous literature seems, at first, to show contrasting evidence. Models based on the incentive of firms to signal their quality, like that of Welch (1989), show evidence that hot markets contain more IPO's of high quality firms. These firms choose hot market conditions as these contain offer prices less affected by adverse selection. Opposite of this, literature as that of Loughran and Ritter (1995) finds that hot markets contain firms that perform poorer over a longer horizon, indicating seemingly poorer quality firms overall.

In assessing the quality of firms in either hot or cold markets, Helwege and Liang (2004) look at factors such as growth potential, current profitability and performance in the years following issuance. In first instance the authors find a distinction in that hot market firms are smaller and have higher market-to-book ratios, pointing towards start-up firms with high growth potential. Yet, once these firms are normalized for industry and macroeconomic conditions the distinctions disappear. Alongside this, they find that distinctions based on the younger age profile of hot market firms also do not hold up when looking over the longer post-IPO horizon. Overall, the authors find few differences in the internal characteristics of IPO firms (profitability, size, growth) in either hot or cold market, except that cold market firms are found to have more capital expenditure. This evidence on the similarity of firms in hot and cold market, along with the fact that firms in hot markets show higher initial returns, points towards investor sentiment stewing up prices.

Other academics, and what is in line with the general theme of this paper, look at how hot markets are linked to bullish optimism of investors and how this creates a window of opportunity for issuers. Lerner (1994) studies this by looking at financing for U.S. biotechnology firms from either private or public sources of capital. He finds a positive relation between IPO volume and the price public investors are willing to pay. Linking this to the phrases used in this paper, the willingness of public investors (in this case venture capitalists) to pay a high price could be seen as a proxy for investor sentiment.

Overall, it seems that literature has found a positive relationship between sentiment, in the form of investor optimism, and IPO activity. There exists a certain predictability in positive hot IPO markets, and the general evidence shows that a correlation between IPO volume and market peaks points towards issuers being able to time their IPO's to benefit from these positive conditions.

3 Hypothesis development

To form the hypothesis for this paper it is important to look at IPO underpricing, in the form of first day returns, from two opposite angles. First of all, there is the angle form the point of view of the issuer and underwriter of an IPO. The aforementioned theory on underpricing incentives suggests that, mostly due to the information asymmetry between issuers and investors, underpricing always persists. Even in hot markets, which evidence shows are predictable (Ibbotson and Jaffe 1975), issuers will aim to underprice their IPO's to deter IPO's of lesser quality (Ritter and Welch 2002) and to maintain the participation of lesser informed investors who would otherwise suffer from the winner's curse (Rock 1986). These incentives of issuers go together with the ever persistent principal agency problem in which underwriters show rent-seeking behaviour by underpricing an IPO to allow certain investors to gain positive initial returns (Ljungqvist 2005).

Opposite to these effects lies the willingness of investors to pay a price above the fundamental value of the issued stock. Evidence shows that IPO firms under-perform over the long-run compared to matched non-IPO firms and this indicates a short-term overpricing by investors above the fundamental value of the firm (Ritter 1991). Furthermore, literature such as that of Deaves et al. (2010) finds that market forecasters, which could proxy for investors, are in general shown to be overconfident. Next to this, in line with the self-attribution bias, they show that forecasters learn from their mistakes but that experienced forecasters are seen to be relatively more overconfident.

Lastly, in the theory on market timing for IPO's, literature states an overall positive relationship between investor sentiment and IPO activity (Rajan and Servaes 1995, Lerner 1994). This coincides with a tested positive correlation between IPO activity and relative market peaks, with issuers trying to capture the benefits of certain windows of opportunity.

To answer this paper's research question on what the effect of investor sentiment is on IPO underpricing, the hypothesis is to find an overall positive correlation between the two. This paper hypothesises than an increase in positive investor sentiment will increase IPO underpricing.

With incentives of issuers to underprice IPO's being persistent in every market setting, the increased willingness to pay a higher price for newly issued stocks by overconfident sentimental investors will increase the spread between offer price and first-day-closing price. In short, because of the ever persistent tendency of issuers to under price stocks and the sentiment of investors stewing up stock prices, I hypothesise that an increase in positive investor sentiment will have a positive effect on IPO underpricing, in the form of high first-day-returns of issued stocks.

4 Data and methodology

This paper will aim to quantify the relationship between investor sentiment and IPO underpricing by performing a series of regression tests. The main regression will incorporate the ARMS-index measure for investor sentiment, along with several control variables for IPO characteristics. Next to this, tests will be conducted to see whether controls for any omitted differences between individual industries and time periods are needed via fixed effects. Results will later be tested for robustness by incorporating different measures for investor sentiment, in the form of the Put/Call-ratio and VIX fear gauge. Subsequently, this paper will aim to indicate a difference in the the level of the correlation between investor sentiment and underpricing between different industries. The following segment will process all proxies used within the regression analyses and robustness tests as well as formulate the regression equation used in this paper.

4.1 IPO underpricing

This paper uses data on a total of $5,499$ different IPO's acquired from the ThomsonOne financial database. The search criteria for these IPO's is quite broad in that it compiles IPO's from January 1990 to as recent as November 2017. Geographically the data is set to incorporate all IPO's on a global scale, from the Western countries down to the emerging markets. The dataset is based on a daily frequency and all trading days within industries that showed multiple IPO's on the same day were consolidated by taking the average values for that day.

IPO underpricing is computed as the ratio between the offer price set by issuers and the closing price after the first day of trading. This first-day-return gives a representation of the money issuers and underwriters 'left on the table' by offering the IPO below the value the market was willing to pay for the stock. The formula for IPO underpricing is shown below:

$$U = \frac{Closing\ Price - Offer\ Price}{Offer\ Price} \tag{1}$$

The dataset shows an overall average U of 34,02%, with a maximum of as high as 4,503.17% and a minimum return of -99,80%. Due to the large amount of data points and the plausible global average, no corrections were made for strong outliers. Next to this, no correction is made to control for the return of an IPO above the return of the market on that specific day. Chen et al. (2004) mention in their paper on the underpricing on the Chinese stock market where they do correct for daily market returns, that replications of their model that leave out this correction yield similar conclusions.

The industry segmentation used in this paper is utilised by the ThomsonOne database and covers the following industries: Consumer Products and Services, Consumer Staples, Energy and Power, Financials, Healthcare, High Technology, Industrials, Materials, Media and Entertainment, Real Estate, Retail, and Telecommunications. Information on the subsequent sub-industries can be found in the appendix (table 2).

4.2 Investor sentiment measures

Literature points out two distinct methods of measuring investor sentiment. One either opts for a direct method, built up out of surveys directly asking investors how they feel about current market situations, or opts for an indirect method, using proxies based on financial data.

Though literature has shown numerous attempts at indirectly quantifying investor sentiment, many of these measures have been subject to debate on their validity when controlled for general market conditions. As mentioned earlier, Campbell et al. (2008) have conducted similar research as this paper, in their attempt at testing for the relationship between investor sentiment and IPO underpricing. These authors also mention the inconsistent results of some sentiment measures and place their faith in the proven measure constructed by Baker and Wurgler (2006, 2007).

Their construction of their sentiment index is based on six different proxies, each controlled for market variables. These are NYSE trading volume, the dividend premium, the amount of IPO's, lagged first-day-returns on IPO's and the equity share in new issues. Campbell et al. (2008) are able to find a positive and significant relationship between their investor sentiment variables and the first-day-return in all their sample regressions.

This paper will attempt to find the same hypothesized positive relationship between investor sentiment and IPO underpricing, but will use other proxies for investor sentiment. The following segment will discuss the construction of the main investor sentiment measure used, the ARMS-index, as well as the Put/Call-ratio and VIX fear gauge which are used to test the robustness of the regression model.

4.2.1 ARMS index

The ARMS index, sometimes referred to as the TRIN (trading index), was constructed by Richard Arms in 1967. Since then, this index has become an important intra-day trading tool computed by market forecasters to analyse the sentiment in the market (Arms 1989). The index is constructed by looking at the number of advancing stocks to the number of declining stocks at a given time, and relates that comparison to the advancing and declining volume at the same instant. It serves as a quick tool to see whether advancing stocks are receiving their fair share of the total trading volume. To estimate the ARMS index this paper uses the following formula:

$$ARMS = \frac{Decline\ Volume/\#\ declining}{Advance\ Volume/\#\ advancing} \tag{2}$$

As Chowdhury et al. (2014) explain, this measure expresses a ratio that captures the 'bullishness' or 'bearishness' of the market. For a bullish market the advancing stocks should receive a higher portion of total volume than their declining counterparts. Due to the construction of the formula, bullishness is therefore expressed in a negative ARMS value. Placing this into the framework set up by this paper, the hypothesis is to find a negative correlation between this ARMS-index measure and IPO underpricing. A negative correlation would mean that an increase in positive industry sentiment would lead to an increase in IPO underpricing.

In applying this index as a measure for investor sentiment, this paper first of all needed to acquire data on stock returns. Practitioners often use data from large stock indices (like the S&P 500) to construct the ARMS measure, yet with the goal of comparing sentiment across different industries in mind, this paper constructed its own industry indices. For this the same aforementioned industry segmentation was used, compiled by the ThomsonOne financial database (see appendix table 2). For each industry a selection of approximately 100 to 200 large cap firms listed on the NYSE, AMEX or NASDAQ stock exchange was made. Stock price data was acquire from the DataStream financial database and stretched over the same time frame as the IPO data, January 1990 to November 2017. Due to their large size and strong diversity, this paper assumes that the selected stocks properly represent their industry's dynamics and fundamentals. To look at the ARMS index over the entire market all indices are combined to form an overall index incorporating 2,026 listed firms.

In this construction this paper computes two variables for investor sentiment in the form of the ARMS-index. The first utilises the entire pool of 2,026 firms ($ARMS$) and thus indicates investors' general sentiment for the entire market. The second computes separate ratios using only the firms from each corresponding industry ($INDARMS$). This second measure thus indicates investors' daily trading sentiment for a particular industry.

4.2.2 Put/Call ratio

In their study, Bandopadhyaya and Jones (2008) conduct a comparative analysis of the validity of two investor sentiment measures. In line with this paper, these are the Put/Call ratio and the VIX fear gauge. The choice to compare these two measures, while there are many other valid options, stems from the ease in which these are accessible. Both ratios are computed daily and stored by the Chicago Board Options Exchange (CBOE). This is also were this paper acquired data for these sentiment measures.

The Put/Call ratio is computed by the CBOE by adding all put and call volumes of individual equities and several indices, such as the S&P 100. This ratio is a very straightforward measure for investors' trading sentiment in the market as a put is a literal bet against a stock and a call is a long positive bet in favour of a stock. The actual equation is quite logically as follows:

$$PCR = \frac{Put\ Volume}{Call\ Volume} \tag{3}$$

Although a value of 1 would typically seem to be a value representing a neutral market, evidence shows that on average trading days a larger number of calls is traded, compared to puts. Therefore a value of around 0.8 is usually considered 'normal', with a value below 0.7 considered 'strong' and optimistic, and a value above 1.1 being considered 'weak' (Bandopadhyaya 2006).

In their comparative analysis, Bandopadhyaya and Jones (2008) find that the Put/Call ratio is a better explanatory variable than the VIX fear gauge. They test this in a random-walk model and find that the Put/Call ratio describes a significant portion of the movements in the S&P 500 index not covered by standard macroeconomic variables.

As mentioned above, this paper acquires data on put and call volume from the Chicago Board Options Exchange. Due to the lack of further available data, the Put/Call ratios offer a timespan from November 2006 to November 2017. The data computes separate ratios for options traded for indices and the equity market, along with a total exchange Put/Call-ratio which is a combination of the two. Seeing as the nature of this research paper is based on

IPO's, focus will be placed on the relationship with the Equity Put/Call ratio, yet the Total market Put/Call-ratio will also be incorporated into the robustness tests.

Table 1: Put/Call ratio statistics

This table shows the amount of days in which each different Put/Call ratio in this paper's dataset (Nov 2006 to Nov 2017) is either 'neutral' ($> 0.7 \& < 1.1$) , 'strong' (< 0.7) or weak (> 1.1)

	Normal	Strong	Weak
Equity Put/Call	3559	1985	8
Index Put/Call	3830	63	1659
Total Put/Call	5036	75	441

Table 1 shows a short summary on the levels of each of these three ratios and the number of days they express either a strong, weak or neutral market. It can be noted that sentiment was strongly bullish in the equity market, especially when comparing it with the index market. This strong difference is said to be due to the fact that professional traders often use index options to hedge their long positions in equity, making these two Put/Call-ratios somewhat contradictory. The 'Total' Put/Call-ratio, which is a combination of the two, will negate this bias.

No adjustment is made to separate this investor sentiment measure over the different industries. Subsequent research is advised to attempt to construct separate equity Put/Call ratios using only equity from a particular industry. For this paper, the general Put/Call ratios are used as overall proxies for investor sentiment. Tests are done to find a correlation with the underpricing (U) of the IPO's in the combined IPO-dataset. These are done to test the robustness of the results following the tests using the ARMS-index as primary sentiment measure.

An increase in positive investor sentiment translates to an increase of total call option volume resulting in a lower Put/Call-ratio. Therefore, in line with the hypothesis set for the relationship between IPO underpricing and investor sentiment, this paper expects to find a negative correlation between first-day-return and the Put/Call-ratio.

4.2.3 VIX fear gauge

The VIX is built up out of investor expectations of the implied volatility of 30-day options of the S&P 100 index. When stock prices decline investors become more fearful, and this translates into a higher level of the VIX. This measure is therefore often dubbed the 'fear gauge' of the market (Arak and Mijid 2006). High levels of the VIX are also linked to low levels of investor sentiment, as in expectation of high volatility investors trade increasingly risk averse and pessimistic (Bandopadhyaya and Jones 2008).

This sentiment measure is often incorporated by academics into their research, such as by Dash and Moran (2005) in their study on hedge fund returns and by Banerjee et al. (2007) in their study on the relationship of the VIX with certain stock portfolios. Yet, the VIX is also a widely accepted measure for investor sentiment used by practitioners.

Similar to the Put/Call ratio, the VIX is computed and acquired from the Chicago Board Options Exchange. Again, due to lack of availability, the timespan of this measure does not reach the entire dataset of IPO's for this paper, but instead spans from January 2004 to November 2017. Similar to the Put/Call ratio, no industry specific measurement is possible for this sentiment index, leading to its overall market-form being used in the IPO panel dataset. The average VIX value for this dataset is 17.17, with a maximum of 80.86 and a minimum of 9.19.

An increase in the level of positive investor sentiment decreases the VIX fear gauge, as expectations of the implied volatility of options lower. Therefore, in line with the hypothesis set for the relationship between IPO underpricing and investor sentiment, this paper expects to find a negative correlation between first-day-return and the VIX fear gauge.

4.3 Underpricing regression

This paper uses a panel data model to explain underpricing. Next to incorporation of the ARMS-index as investor sentiment measure the model includes several variables to control for IPO firm-characteristics. These variables are mostly based on the underlying profitability and financials of the firm going public. The model used is as follows:

$$U = \beta_0 + \beta_1 ARMS + \beta_2 REV + \beta_3 EBITDA + \beta_4 MARG + \beta_5 LNASS + \beta_6 EPS + \beta_7 OVER + \sum_{i=8}^{18} \beta_i IND \tag{4}$$

where U, the underpricing of the IPO in the form of the first-day-return; $ARMS$, the investor sentiment measure using the complete selection of 2,026 firms from all industries (will be switched out for $INDARMS$ which uses only firms from the corresponding industry of the IPO'ed firm); REV, the revenue of the firm before offering in millions of USD; $EBITDA$, the EBITDA of the firm before offering in millions of USD; $MARG$, the EBITDA margin to revenue of the firm before offering as an indication of firm profitability; $LNASS$, the natural log of total assets of the firm before offering; EPS, the average earnings per share of the firm in the twelve months proceeding the offering; $OVER$, a dummy variable indicating whether there was oversubscription for shares of the IPO exceeding the offered amount of shares; IND, the fixed effect industry dummy variable. The 11 dummies are Consumer Staples (β_8), Energy & Power (β_9), Financials (β_{10}), Healthcare (β_{11}), High Technology (β_{12}), Industrials (β_{13}), Materials (β_{14}), Media & Entertainment (β_{15}), Real Estate (β_{16}), Retail (β_{17}) and Telecommunications (β_{18}). The Consumer Products & Services industry is captured in the intercept term. Further industry segmentation can be seen in appendix table 2. Data of the independent variables was acquired from the ThomsonOne database together with all IPO data. Descriptive statistics of the independent variables used can be seen in appendix table 3.

Due to the nature of the dataset to include 2,802 unique dates on which IPO's were issued this paper chooses not to control for time fixed effects by adding in time dummy variables. Adding 2,801 dummy variables will lower the degrees of freedom of the regression model and increase the risk of over-fitting the model. Yet, this paper will conduct tests surrounding the effect of implementing a time fixed effect to the regression model.

As mentioned before, the expectation of this paper is to find a positive correlation between an increase in positive investor sentiment and the level of IPO underpricing. Due to the construction of the $ARMS$ measure to decrease following an increase in positive sentiment, the hypothesis statement is as can be seen below. Regressions tests conducted in this paper will attempt to reject the null-hypothesis.

$$H_0 : \beta_1 \geq 0$$

$$H_A : \beta_1 < 0$$

4.4 Industry comparison

Another aspect of this research paper is to test whether there are differences in the effects of the correlation between underpricing and investor sentiment within different industries. To test this the paper will run regressions on a sub-sample of two different industries and look for evidence indicating a difference in the slope coefficient for the $ARMS$ variable (β_1) and look for significance of dummy variable fixed effects when placing IPO data of these two industries into a panel regression.

Appendix table 4 shows summary statistics of the level of underpricing, in the form of the first-day-return, of all 12 industries over the period of January 1990 to November 2017. It is immediately interesting to point out that the amount of IPO's (observations) during this period varies quite substantially. The High Technology sector saw the largest amount of IPO's during this period (967) while telecommunications showed the least (190). When it comes to average underpricing it stands out that the Real Estate industry shows the lowest level of first-day-returns. Its average of 9,42% is also far below the aforementioned overall average of the entire dataset of 34,02%. It is therefore that this paper chooses the Real Estate Industry as one of the industries in the sub-sample.

On the other end this paper chooses the High Technology industry. This due to the fact that it is in the higher end of the average underpricing range, with 36,78%, and shows the largest volume of IPO activity. Also, the period used for this paper (January 1990 to November 2017) incorporates the so-called internet-bubble of the late 1990's. This period is generally linked to an exuberant amount of positive investor sentiment towards everything internet related, and these types of firms fall within this industry class (see appendix table 2).

5 Empirical results

This segment will discuss the results following the regression analyses conducted to test for the relationship between IPO underpricing, in the form of the first-day-return, and investor sentiment. First, results from regressions using the main measurement for investor sentiment, the ARMS-index, will be discussed. Next, these results will be tested for robustness by swapping the investor sentiment measure for the Put/Call-ratio and VIX fear gauge. Lastly, a sub-sample analysis for the High Technology and Real Estate industry will be conducted to test for differences in the correlation between underpricing (U) and investor sentiment ($ARMS$).

5.1 Regression results

5.1.1 ARMS ratio regression

First, as a general indication of the correlation between underpricing and the ARMS-index, appendix table 5 shows the results of a simple regression with no extra independent variables. From this basic model we see that the $ARMS$ variable shows a low yet slightly positive correlation with IPO underpricing (U). This parameter estimate of β_1 of 0,0321 shows statistical significance at the 0.05 significance level. Next to this, when conducting the same simple regression model with the $INDARMS$ measure we find a redundantly low and negative estimate which is found to be insignificant at either the 0.05 or 0.1 significance level. Though the F-test score of the model using the $ARMS$ has a p-value lower the 0.05 level of significance, we see that the goodness-of-fit of this model is extremely low with the R^2 being just 0.07%.

Moving from this overly simplified model, extra independent variables are added controlling for IPO characteristics. The first column in appendix table 6 shows the result of running a standard OLS model regression. We see that the parameter estimate of β_1 for $ARMS$ slightly drops in respect to the simple model in table 5. Also its p-value increases slightly allowing it to only be accepted at the 0.1 level of significance. The profit based independent variables for Revenue, EBITDA, EBITDA-margin and Earnings Per Share all show very low explanatory power towards underpricing and are not found to be significant at either the 0.05 or 0.1 level. The parameter estimate of β_5, for the natural logarithm of total assets of the firm before offering, shows strong significance at the 0.01 level and a negative coefficient. This indicates that an increase in firm size, in the size of total assets, decreases the level of IPO underpricing. The goodness of fit of this extended model increases slightly with regard to the earlier model, to an R^2 of 0.6%, yet this is still extremely low pointing to some omitted variables and effects that still need to be added to the model.

The second column in appendix table 6 shows the model incorporating dummy variables for industries and their parameter estimates of $\beta_8 - \beta_{18}$. Methodologically the addition of this industry fixed effect makes sense as it controls for the individual differences between the industries which would otherwise lead to omitted variable bias. The implementation of this industry fixed effect assumes that the individual-specific effects are correlated with the independent variables. Seeing as that the industries, and the companies that form them, are inherently different in many ways, the addition of such an effect seems theoretically sound.

Interestingly enough, the addition of these dummy variables seems to have little effect upon the earlier model. The estimate of β_1 shows little to no difference still being positive and statistically significant at the 0.1 level. Next to this, it seems no dummy variable coefficient reaches statistical significance. When conducting an F-test on the hypothesis that the coefficients of all dummy variables are jointly zero ($H_0 : \beta_1 - \beta_{18} = 0$) a score of 1.44 and a corresponding p-value of 0.15 are found, not allowing for the rejection of the null-hypothesis. Though this would indicate the industry fixed effects to have no statistical significant effect upon underpricing, their addition does slightly increase the goodness-of-fit of the model and their incorporation is theoretically sound.

Alongside this fixed effect for industries, the independent variables may have a correlation with the omitted effects of individual differences between points in time. Methodology would point to the need to incorporate a time fixed effect, in the form of dummy variables for time. Yet, due to unbalanced nature of the panel data used in this paper, with IPO's being on seemingly random dates in time and across industries, this is not a straightforward task.

As mentioned earlier, the dataset incorporates 2,802 unique dates on which IPO's were issued. The third column in appendix table 6 shows the results of a regression model incorporating 2,801 unique time dummies, next to the earlier used variables in model 2 of table 6. As expected, the addition of this amount of variables strongly diminishes the degrees of freedom and the F-test of the model gives a score of 0,86 and a corresponding p-value of 1,0 not allowing the rejection of the hypothesis which states that this model is the same as its intercept-only counterpart with no predictors. We do finally see a larger level of explanatory power in a R^2 of 0,47, yet this value is highly inflated due to large number of added time dummy variables.

5.1.2 Robustness measures

To test the robustness of the results from the regressions using the $ARMS$ variable as investor sentiment measure, this paper conducts the same tests using different sentiment measures. Appendix table 7 shows the results of three regression models constructed in similar fashion as the second model in table 6 (see appendix). Each of the three models incorporates industry dummy variables to control for individual-specific differences between industries.

The first sentiment measure used is the total Put/Call-ratio, computed from data from both equity- and index-based options ($TOTPC$). Evidence shows a positive coefficient of β_1 for this investor sentiment measure which is found to be significant at the 0.1 level. Next to this, in contrast to earlier tests using the ARMS-index, several industry dummy variables reach statistical significance and the F-test testing the hypothesis that all dummy variable coefficients are jointly zero ($H_0 : \beta_1 - \beta_{18} = 0$) can be rejected at the 0,05 level. This indicates a significant effect for the industry fixed effect within this model and strengthens the claim for its theoretical soundness.

The second model in appendix table 7 utilises the equity Put/Call-ratio ($EQPC$) as measure for investor sentiment. This measure solely uses equity based options in its calculation. In similar fashion as in the model using the $TOTPC$ variable, several dummy variables reach statistical significance. Yet, in contrast, the positive parameter estimate for the investor sentiment measure (β_1) does not reach statistical significance at either the 0.05 or 0.1 level.

Lastly, the third model using the VIX fear gauge as measure for investor sentiment also does not reach statistical significance for its β_1 coefficient.

5.2 Industry comparison

In this segment three different regression tests are conducted to test for differences in the relationship between the ARMS-index and underpricing regarding two industries. As mentioned earlier, these are the High Technology and the Real Estate industry. Table 8 in the appendix first of all shows a first model using solely the 967 total IPO's in the High Technology industry. The model finds a positive coefficient of 0,1609 (β_1) relating to the correlation of the ARMS-index measure with IPO underpricing within this sub-sample. The coefficient is found to be strongly significant at the 0.01 level of significance. Regrettably, when using the data on the 260 IPO's in the Real Estate industry, no significant relation is found for the ARMS-index with IPO underpricing in the second model. Yet, it is interesting to point out that the estimate of β_1 is negative in the second model where it was positive in the model using High Technology IPO's. Both separate models show a goodness-of-fit (R^2) of just above 2%.

When testing in a sub-sample combining IPO's of both industries (table 8 model 3) again a positive correlation coefficient is found for the relationship between the ARMS-index and first-day-return of the IPO's. This model also incorporates a dummy variable for all IPO's from the Real Estate industry and the estimate gives a negative coefficient of -0,2186 which is found to be significant at the 0.05 level. This translates into IPO's from the Real Estate industry having a lower base value (holding all variables constant) as compared to IPO's from the High Technology industry (which is captured in the model's intercept value).

6 Conclusion

This paper set out to test for the correlation between IPO underpricing and investor sentiment. The first was quantified in the form of the spread between the offer price set by issuers and the closing price of the stock after the first day of trading, in the first-day-return. The second, investor sentiment, was quantified by constructing several proxies based on financial data.

Firstly, the ARMS-index captured investor sentiment in the ratio of the trading volume put into declining stocks over the number of declining stocks, divided by the ratio of the volume put into advancing stocks over the number of advancing stocks. A negative ratio indicates that investors put more trade volume into stocks that are in an upswing, symbolizing their positive (bullish) sentiment towards the market. This paper divided the market into 12 separate industries and built up proxy indices out of a selection of around 100 to 200 stocks per industry. These indices were used in the construction of the ARMS ratio, which is used as this paper's main measure for investor sentiment. Alongside this, investor sentiment was computed as the Put/Call ratio and VIX fear gauge to be used to test the robustness of the regression results.

This paper hypothesised that an increase in positive investor sentiment would lead to an increase in IPO underpricing. Initial regression tests using the overall market $ARMS$ variable produced a positive estimate for this coefficient. This was found to be significant at the 0.1 level, while controlling for several IPO characteristics and for industry fixed effects. Due to the nature of the ARMS-ratio to decrease following an increase in positive investor sentiment, these test results found early evidence in favour of this paper's null-hypothesis ($H_0 : \beta_1 \geq 0$).

Subsequent regression models incorporating different proxies for investor sentiment found significant results at the 0.1 level for the correlation between IPO first-day-return and the total Put/Call-ratio for options of both equity and indices. Similar to that of the ARMS-index measurement, a positive correlation coefficient was found for this investor sentiment proxy. Due the construction of the Put/Call-ratio, this result similarly points to IPO underpricing decreasing following an increase in positive investor sentiment.

From a theoretical standpoint this relationship could make sense as issuers are able to time their IPO's to coincide with market peaks and thus choose to price their stock relatively higher. This would close the spread between offer price and first-day-closing price paid by sentimental investors. From a statistical standpoint, this paper was not able to find evidence to reject the null-hypothesis. Alongside this, the low level of confidence surrounding the positive correlation coefficients found, being only significant at the 0.1 level, as well as the low goodness-of-fit of the models used, leaves ample room for further research to improve the explanatory power of the models. In tests aiming to find a difference in the correlation of investor sentiment with underpricing between different industries this paper compared the High Technology and Real Estate industry. The slope coefficients found were contradictory, yet only the positive coefficient in the High Technology industry was found to be significant. Next to this, Real Estate firms were found to have a significantly (at the 0.01 level) lower base-level of underpricing within the sub-sample dataset.

Subsequent research is requested to delve deeper into the apparent two-sided phenomenon of IPO underpricing, in the form of the first-day-return. In the face of investor sentiment, issuers might be able to profit by setting a higher offer price, yet this might also be negated by sentimental investors being even more willing to pay a higher price. It would be interesting to quantify and directly test the relationship between these two effects.

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Appendix

Table 2: Industry segmentation

This table shows the industry segmentation used in this paper, constructed by the ThomsonOne database

Consumer Products and Services	Educational services	Industrials	Aerospace & Defense
	Home furnishings		Automobiles & Components
	Legal services		Building/Construction & Engineering
	Other consumer products		Machinery
	Professional services		Other Industrials
	Travel services		Transportation & Infrastructure
Consumer Staples	Agriculture and livestock	Materials	Chemicals
	Food and Beverage		Construction Materials
	Household & Personal Products		Metals & Mining
	Textiles & Apparel		Other Materials
	Tobacco		Paper & Forest Products
Energy and Power	Alternative Energy Sources	Media and Entertainment	Advertising & Marketing
	Oil & Gas		Broadcasting
	Other Energy & Power		Cable
	Petrochemicals		Casinos & Gaming
	Pipelines		Hotels and Lodging
	Power		Motion Pictures / Audio Visual
	Water and Waste Management		Publishing
Financials	Alternative Financial Investments		Recreation & Leisure
	Asset Management	Real Estate	Non Residential
	Banks		Other Real Estate
	Brokerage		Real Estate Management & Development
	Credit Institutions		REITs
	Diversified Financials	Retail	Apparel Retailing
	Insurance		Automotive Retailing
	Other Financials		Computers & Electronics Retailing
Healthcare	Biotechnology		Discount and Department Store Retailing
	Healthcare Equipment & Supplies		Food & Beverage Retailing
	Healthcare Providers & Services		Home Improvement Retailing
	Hospitals		Internet and Catalog Retailing
	Pharmaceuticals		Other Retailing
High Technology	Computers & Peripherals	Telecommunications	Other Telecom
	E-commerce / B2B		Space and Satellites
	Electronics		Telecommunications Equipment
	Internet Software & Services		Telecommunications Services
	IT Consulting & Services		Wireless
	Other High Technology		
	Semiconductors		
	Software		

Table 3: Descriptive statistics of independent variables

The following table shows summary statistics of all time-variant independent variables used in the regression model. These are: $ARMS$, investor sentiment measure which computes the proportion to which declining stocks receive their share of total trade volume as compared to increasing stocks; $INDARMS$, ARMS measure focussing on the particular industry in which the IPO'ed firm is positioned; REV, the revenue (in millions of USD) of the firm before offering; $EBITDA$, the EBITDA (in millions of USD) of the firm before offering; $MARG$, the EBITDA-margin to revenue of the firm before offering as an indication of firm profitability; $LNASS$, the natural log of total assets of the firm before offering; EPS, the average earnings per share (in USD) of the firm in the twelve months proceeding the offering. The time frame for all variables is January 1990 to November 2017.

Variable	Mean	Median	Standard deviation	Minimum	Maximum
$ARMS$	1.19	0.94	1.16	0.02	16.78
$INDARMS$	2.19	0.95	13.11	0.00	632.45
REV	440.17	61.20	2,523.81	-826.00	79,985.30
$EBITDA$	76.61	10.40	540.06	-831.30	28,733.80
$MARG$	-0.29	0.17	13.10	-318.00	772.33
$LNASS$	4.38	4.16	1.87	-2.30	13.07
EPS	2,098.35	0.04	143,308.15	-1,925.29	10,609,676.06

Table 4: Underpricing statistics per industry

This table shows summary statistics of the level of IPO underpricing of a total of 5,499 firms going public in 12 different industries over the period of January 1990 to November 2017. Underpricing is calculated as the first-day-return, which is the spread between the price of the stock at offering and the price at closing of the first trade date.

Industry	Number of observations	Mean underpricing (%)	Median underpricing (%)	Standard deviation (%)	Minimum underpricing (%)	Maximum underpricing (%)
Consumer Products & Services	445	37.66%	10.88%	205.19%	-99.51%	4,010.53%
Consumer Staples	393	36.78%	12.05%	128.55%	-37.86%	1,511.54%
Energy & Power	322	40.18%	10.07%	266.80%	-91.23%	4,503.17%
Financials	375	34.56%	7.82%	188.67%	-92.49%	2,513.64%
Healthcare	502	29.63%	10.98%	69.30%	-91.18%	725.53%
High Technology	967	36.78%	12.68%	137.97%	-96.72%	3,605.67%
Industrials	876	42.22%	16.38%	128.27%	-98.97%	1,915.63%
Materials	595	32.87%	17.74%	52.48%	-99.80%	391.11%
Media & Entertainment	264	28.45%	8.27%	91.59%	-46.53%	966.67%
Real Estate	260	9.42%	2.83%	30.76%	-99.35%	213.58%
Retail	310	30.58%	13.49%	55.84%	-35.12%	539.13%
Telecommunications	190	23.91%	7.71%	91.68%	-99.02%	1,137.84%

Table 5: Basic ARMS regression

This table shows the regression under simple OLS assumptions that tests for the relationship between IPO underpricing, in the form of the first-day-return, and investor sentiment. Investor sentiment is captured in the ARMS-index measure which computes the proportion to which declining stocks receive their share of total trade volume as compared to increasing stocks. The $ARMS$ variable uses stock return data of a total 2,026 firms across all industries and the $INDARMS$ variable is industry specific.

VARIABLES	*U*	*U*
ARMS	0.0321**	-
	(0.016)	
INDARMS	-	-0.0007
		(0.001)
Constant	0.3093***	0,3492***
	(0.027)	(0.019)
Observations	5,499	5.499
R-squared	0.0007	0.0000
F-test model	4.01	0.24
p-value F-test	0.045	0.623

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

Table 6: ARMS regression additions

This table shows regression models based on the relationship between underpricing, in the form of IPO first-day-return, and investor sentiment, in the form of the ARMS-index. The ARMS measure computes the proportion to which declining stocks receive their share of total trade volume as compared to increasing stocks. Equation (1) introduces independent variables to control for IPO characteristics; REV, the revenue (in millions of USD) of the firm before offering; $EBITDA$, the EBITDA (in millions of USD) of the firm before offering; $MARG$, the EBITDA-margin to revenue of the firm before offering as an indication of firm profitability; $LNASS$, the natural log of total assets of the firm before offering; EPS, the average earnings per share (in USD) of the firm in the twelve months proceeding the offering; $OVER$, dummy variable whether their was over-subscription of the equity. Equation (2) introduces dummy variables for 11 different industries with the Consumer Products & Services industry being captured in the intercept term. Equation (3) incorporates 2,801 dummy variables for time periods controlling for time fixed effects.

VARIABLES	(1) U	(2) U	(3)time U
$ARMS$	0,0281*	0,0282*	-0.2702
	(0.016)	(0.016)	(2.560)
REV	7,28e^{-7}	-3.37e^{-7}	-3,10e^{-6}
	(0.000)	(0.000)	(0.000)
$EBITDA$	1,74e^{-6}	2,92e^{-6}	0.0000
	(0.000)	(0.000)	(0.000)
$MARG$	0.0008	0.0008	0.0009
	(0.001)	(0.001)	(0.002)
$LNASS$	-0,0539***	-0,0559***	-0,0663***
	(0.011)	(0.011)	(0.018)
EPS	-3,83e^{-8}	-3,81e^{-8}	-8,00e^{-8}
	(0.000)	(1,30e^{-7})	(1,92e^{-7})
$OVER$	-0.0242	-0.0166	0.1102
	(0.062)	(0.062)	(0.098)
Constant	0,5525***	0,5533***	0.4242
	(0.054)	(0.082)	(2.343)
d.Consumer Staples	-	0.0374	-0.0192
d.Energy & Power	-	0.1088	0.1065
d.Financials	-	0.0740	0.0747
d.Healthcare	-	-0.0713	-0.1556
d.High Technology	-	-0.0030	-0.1022
d.Industrials	-	0.1080	0.0981
d.Materials	-	0.0018	-0.0280
d.Media & Entertainment	-	-0.0702	-0.2614
d.Real Estate	-	-0.1785	-0.2013
d.Retail	-	-0.0322	-0.1634
d.Telecommunications	-	-0.0944	-0.0815
Observations	5,499	5.499	5.499
R-squared	0.0060	0.0089	0.4749
F-test model	4.76	2.74	0.86
p-value F-test	0.000	0.000	1.000

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

Table 7: Robustness regressions

This table shows panel regression models testing for the relationship between IPO first-day-return (U) and several measures for investor sentiment. $TOTPC$ is an investor sentiment proxy computing Put/Call-ratio's based on equity and index options. $EQPC$ is a Put/Call-ratio based solely on equity options. VIX is built up out of investor expectations of the implied volatility of 30-day options of the S&P 100 index. Other independent variables control for IPO characteristics: the revenue (REV), EBITDA ($EBITDA$), EBITDA-margin ($MARG$) and natural log of total assets ($LNASS$) as well average earnings per share (EPS) 12 months prior to offering of the firm and a dummy variable indicating whether there was oversubscription of the stock ($OVER$). Additionally, 11 dummy variables for industries are added with the Consumer Products & Services industry being captured in the intercept.

VARIABLES	(1) U	(2) U	(3) U
$TOTPC$	0,2365*		
	(0.142)		
$EQPC$		0,0815	
		(0.203)	
VIX			-0,0034
			(0,003)
REV	$3{,}79e^{-6}$	$3.85e^{-6}$	$1{,}16e^{-6}$
	(0.000)	(0.000)	(0.000)
$EBITDA$	$7{,}52e^{-6}$	$6{,}38e^{-6}$	$4{,}54e^{-6}$
	(0.000)	(0.000)	(0.000)
$MARG$	0.0006	0.0006	0.0008
	(0.001)	(0.001)	(0.001)
$LNASS$	-0,0797***	-0,0801***	-0,0642***
	(0.014)	(0.014)	(0.012)
EPS	$-3{,}46e^{-8}$	$-3{,}64e^{-8}$	$-3{,}57e^{-8}$
	$(1{,}29e^{-7})$	$(1{,}29e^{-7})$	$(1{,}27e^{-7})$
$OVER$	0,0548	0,0563	-0,0146
	(0.062)	(0.078)	(0.062)
Constant	0,4009**	0,5765***	0.7053***
	(0.054)	(0.165)	(0,097)
d.Consumer Staples	0,1180	0.1163	0,0132
d.Energy & Power	0,2475**	0.2428**	0.1035
d.Financials	0,2115*	0.2115*	0.0581
d.Healthcare	-0,0203	-0,0236	-0,1140
d.High Technology	0,0691	0,0669	-0.0522
d.Industrials	0,2361**	0.2336**	0.0992
d.Materials	0,0681	0.0666	-0,0220
d.Media & Entertainment	0,0371	0,0353	-0,0760
d.Real Estate	-0,1144	-0,1154	-0.1859
d.Retail	0,0328	0,0322	-0.0429
d.Telecommunications	0,0601	0,0573	-0.0922
Observations	3.806	3.806	4.933
R-squared	0.0149	0.0142	0.0103
F-test model	3,18	3,03	2,83
p-value F-test	0,000	0,000	0,000

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

Table 8: Industry comparison regressions

This table shows regression models based on the relationship between underpricing, in the form of IPO first-day-return, and investor sentiment, in the form of the ARMS-index. The ARMS measure computes the proportion to which declining stocks receive their share of total trade volume as compared to increasing stocks. Model (1) uses IPO data of the High Technology industry, model (2) uses IPO data of the Real Estate industry and model (3) uses panel data on a combination of the two. Model (3) controls for individual-specific differences between the industries by adding a dummy variable for the Real Estate industry. Base value for the High Technology industry is captured in the intercept term.

VARIABLES	(1) *U*	(2) *U*	(3) *U*
If High Technology $ARMS$	0,1609***		
	(0.036)		
If Real Estate $ARMS$		-0.0139	
		(0.018)	
Panel $ARMS$			0,1341***
			(0.029)
REV	$6.83e^{-6}$	$1{,}56e^{-6}$	$1{,}90e^{-6}$
	(0,000)	$6{,}90e^{-6}$	(0,000)
EBITDA	-0.0001	$6{,}96e^{-6}$	-0.0001
	(0.001)	(0,000)	(0,000)
MARG	0.0096	-0.0001	0.0001
	(0.021)	(0,000)	(0.002)
LNASS	-0.0307	-0,0198*	-0.0246
	(0.035)	(0.012)	(0.026)
EPS	$-3{,}52e^{-8}$	-0.0001	$-3{,}50e^{-8}$
	$1.32e^{-7}$	(0,000)	$1.18e^{-7}$
OVER	-1.1844	-0.0416	-0.0123
	(0.187)	(0.051)	(0.131)
Constant	0,3072**	0,2297***	0.3135***
	(0.139)	(0,070)	(0.107)
d.Real Estate	-	-	-0,2186**
	-	-	(0.101)
Observations	967	260	1.227
R-squared	0.0234	0.0218	0.0275
F-test model	3.29	0.80	4.30
p-value F-test	0.002	0.587	0.000

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