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CHOOSING WISELY: STOCK TICKER CHARACTERISTICS AND THEIR EFFECT ON TRADING VOLUME AND COMPANY VALUATIONS

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Preface and acknowledgements

As this is my master thesis, this is the climax of five years of studying Economics, Business Economics and Financial Economics. The last five years have been very challenging but therefore also very rewarding. Although I am highly interested in finance, it was a challenge to come up with a thesis in which I could incorporate aspects of different fields of research. In this thesis, I believe I wrote an interesting paper incorporating aspects from the fields of finance, psychology and even some linguistics. Although the process of writing the thesis has not been without obstacles, I look back at an enjoyous project. Therefore, I want to express my gratitude to Dr. Jan Lemmen, who as supervisor gave me critical feedback and tips that undoubtly enhanced the academic quality of the thesis.

Last but not least, I want to express my deepest gratitude to my family and friends that have been a constant support, sparring partner and inspiration, not only throughout this thesis process but especially throughout my whole studies. A special word of gratitude has to go to my parents who have provided me with all resources necessary, in whatever sense, that have made these years unforgettable and successful.

Abstract

This paper focusses on the potential attention-grabbing effect of certain stock ticker characteristics. It is hypothesized that shorter ticker, tickers that are an English word, tickers that are pronounceable and tickers that are higher in alphabetical listings receive more investor attention. As a result, these companies might enjoy higher trading volume and higher valuations. This is tested using a framework by Durham & Santhanakrishnan (2016) that assumes increased speculation in times of higher investor sentiment, partly due to the increased activity of noise trading individual investors. Therefore, stocks that enjoy more investor attention should be more inflated during times of increasing investor sentiment. It turns out that in times of higher investor sentiment, certain ticker characteristics seem lead to higher trading volume. When testing whether companies with certain ticker characteristics are more deflated during the fall in investor sentiment from December 2021 to June 2022, it is found that the most prominent effect is found for the stock ticker being an English word. The effects of the ticker characteristics sometimes differ among different firm sizes.

Keywords: Behavioral finance, investor sentiment, stock tickers, trading volume, company valuations
JEL Classification: G12, G14, G40, G41

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1 Introduction

Throughout the last decades extensive academic literature has proven that the efficient market hypothesis does not hold. As the efficient market hypothesis argues that investors are fully rational and make decisions based on all information in order to pick stocks or to build portfolios (Joo & Durri, 2018), the extensive amount of empirical work in the field of behavioral finance has proved otherwise. Investors are subject to various decision-making biases which stem from systematic errors in judgment (Chen et al., 2004). Another important phenomenon in behavioral finance is that individual investors are net buyers of stocks in the news, stocks experiencing high abnormal trading volume, and stocks with extreme one-day returns (Barber & Odean, 2008). They hypothesize that many investors only consider stocks that have first caught their attention as attention is a scarce resource. Similar findings are found using Super-Bowl commercials (Fehle et al., 2005) and stocks that were named in TV shows (Engelberg et al., 2012). Since investors' attention is limited and investors do not have the cognitive abilities to assess all stocks as potential investment options, they are likely to prefer stocks that have fluent, understandable names or tickers (Alter & Oppenheimer, 2006). Some company name or ticker characteristics have been researched before, such as pronounceability (Alter & Oppenheimer, 2006), fluency (Head et al., 2009; Green & Jame, 2012) and alphabetical bias (Jacobs & Hillert, 2015; Itzkowitz et al., 2016). Montone et al. (2023) show that companies with more fluent names yield higher market-adjusted returns than companies with less fluent names and that this effect is concentrated among the smaller companies. A generally accepted explanation is that the fluency works as an attention-grabbing characteristic (Montone et al., 2023). Some research focuses on company names and not yet on tickers (Green & Jame; 2012; Montone et al., 2021), some experiments contradict each other (Alter & Oppenheimer, 2006; Peterburgsky, 2017) and a case study that studies multiple ticker characteristics at once seems to be missing. Therefore, the aim of this research is to find ticker characteristics that affect trading activity and company valuations in one big case study inspired by the article of Durham and Santhanakrishnan (2016). Therefore, the main research question of this paper states:

'How do stock ticker characteristics affect trading activity and company valuations?'

Thesis paper examines whether some ticker characteristic that could have an attention-grabbing effect also affect the company's trading volume and valuation. The ticker characteristics focused on in this are the ticker length, whether the ticker is an English word, pronounceability and alphabetical bias. This paper examines the potential effect these characteristics have on trading volume and valuation in a special case study using the fall of investor sentiment from December 2021 to June 2022. The usage of such case study is inspired by the work of Durham and Santhanakrishnan (2016). They show that companies with fluent tickers have lower returns during a period preceded by high investor sentiment. The rationale behind such study is that when investor sentiment is high there is a lot of speculation in the market. This leads to higher overinflation of companies with more fluent tickers as they enjoy higher investor attention. As these companies are more heavily overinflated, their returns are lower in the subsequent periods. In this paper, this framework by Durham and Santhanakrishnan is used to examine the potential effects of other ticker characteristics. This is done using companies that are primary listed on the New York Stock Exchange or the Nasdaq. This data is used to generate two datasets: one for the tests on trading volume and one for the tests on changes in valuations. This is done to keep as many as observations possible while eliminating all observations for which we do not have all values of the control variables. In addition to OLS regressions, mixed-effects regressions are used in order to examine whether the potential effect are persistent in different firm sizes.

From the performed tests to find a potential effect of ticker characteristics on trading volume, it turns out that there is no evidence indicating that ticker characteristics could be affecting trading volume to some extent. From the tests focusing on the change in market capitalization, it appears that ticker length negatively affects these changes instead of positive. Meaning that in times of declining investor sentiment, companies with longer tickers seem to be more heavily deflated. From the performed regressions it turns out that a ticker being a word negatively affects these changes in the full data set. This effect remains highly significant also when the other ticker characteristics are included. Effectively meaning that in times of declining investor sentiment, companies with tickers that resemble an English word seem to be more heavily deflated. When including interaction effect for firm size, the effect was found to be only significant among the smallest 20% of companies. Furthermore, it turns out that a ticker being pronounceable does not affects these changes in the market capitalization. In the test using interaction effects with the Size Quintiles, no significant effect was found. The fourth and last ticker characteristic examined was alphabetical ranking. From the tests using groups for the top 1%, 5%, 10%, 20% and 50%, it seems like there is no evidence indicating that alphabetical ranking could be affecting changes in market capitalization to any extent. From the tests focusing on the change in market capitalization, it turns out that a ticker being in the top 1% actually could lead to more negative changes in the market capitalization during a downfall of investor sentiment, in line with the hypothesis. This effect is significant at the 1% significant level.

In the next chapter (Chapter 2) the current academic literature is examined. It is important to discuss all crucial concepts in order to understand why this case study should work. This is done by first introducing behavioral finance and noise traders. Thereafter, the link between investor sentiment and noise trading is explained and motivated by empirical literature. The concept of investor attention and its link to noise traders and investor sentiment is explained and it is motivated why certain ticker characteristics could lead to higher valuations. At the end of Chapter 2, the predictions of the academic literature are translated into hypotheses. Chapter 3 will then focus on the dataset, including the motivation of the data sample, motivations for the control variables, the summary statistics and the data transformations. Chapter 4 describes the used methodology. This includes the full regression equations and a description of how the mixed effects between ticker characteristics and firm size are examined. Chapter 5 contains the regression results and interpretation of the result. In addition, it includes a discussion whether the hypotheses will be rejected or not. Chapter 6 then presents the conclusion of this paper and the limitations and recommendations for future research.

2 Theoretical framework and hypotheses

2.1 Theoretical framework

To understand how tickers might influence trading activity and company valuations, it is important to discuss the most important background literature. This will be done by covering noise traders, investor sentiment and investor attentions. These topics will help to understand how irrational behavior could lead to higher trading activity and company valuations. Although this paper does not aim to examine the influence of investor sentiment, understanding the role of investor sentiment and noise traders will help to motivate the methodology. Thereafter, these topics will be related to company names and stock tickers. Lastly, this chapter will end with the forming of testable hypotheses.

2.1.1 Introduction to behavioral finance and noise traders

Conventional finance theory often assumes the Efficient Market Hypothesis (EMH) is valid. According to the EMH investors act rationally and make decisions based on all information in order to pick stocks or to build portfolios (Joo & Durri, 2018). The EMH posits that investors are rational and consider all relevant information when making investment decisions and that prices reflect all available information, with changes in prices only occurring in response to new information (Joo & Durri, 2018). This information efficiency implies that it is impossible for market participants to consistently outperform the market (Fama, 1965). However, numerous studies have been conducted over the years that have called into question the validity of these assumptions. These studies have demonstrated that the EMH does not hold and that investors are subject to various decision-making biases. These biases stem from heuristic simplifications, which are systematic errors in judgment (Chen et al., 2004). Behavioral finance, a field that combines behavioral economics and finance, aims to identify and explain these systematic decision errors. For this research we will focus on related phenomena in behavioral finance: noise traders, investor sentiment and investor attention.

An import aspect of behavioral finance that needs to be explained is the concept of noise traders, who engage in trading even though they would be better off not to (Black, 1986). These traders may believe they are trading on useful information, when in fact they are trading on noise, or they may simply enjoy trading. Such noise trading leads to excessive trading and speculation (Vitale, 2000). Consequently, asset prices might diverge significantly from their fundamental values (De Long et al., 1990). De Long et al. (1990) also found that noise traders might steer asset prices in certain directions, even when other traders are still acting rationally. Additionally, active noise traders are a contributing factor to asset price volatility, as they tend to overinflate asset prices during bullish times and excessively deflate them during bearish times. Furthermore, noise traders are often drawn to the hype (CFI, 2023). Typically, noise traders do not have professional backgrounds in finance.

2.1.2 Noise traders and investor sentiment

As explained earlier, Baker & Wurgler (2007) define investor sentiment as the general expectations and beliefs about investment risks and cash flows of financial securities and markets that are not justified by the facts in hands of the public. Increasing investor sentiment means that these expectations and beliefs are increasingly positive and vice versa. As argued by De Long et al. (1990), strong sentiment among noise trades might result in stronger divergence between stock prices and fundamental values. Positive sentiment might also lead to higher expected returns among investors (Haritha & Rishad, 2020). This might lead to increased speculation. Naive investors might potentially underestimate both idiosyncratic risk as well as systemic risk. The eagerness to trade and misjudgment of risks might be amplified through overconfidence. When investors experience gains, they might think that they possess superior investment skills, even when the market returns are not exceeded (Czaja & Röder, 2020). This is due to the self-attribution bias. Furthermore, overconfidence might lead to overestimation of the precision of the available information (Barber & Odean, 2000). This might result in miscalibration and too optimistic views on the potential gains of an investment. This phenomenon is not only limited to individual investors but is observable in the whole market (Statman, Thorley and Vorkink, 2006; Daniel & Hirshleifer, 2015). Consequently, noise traders and overconfident investors might cause stronger divergence between asset prices and their fundamental values. This could increase the volatility in the market. On the other hand, a decrease in the market sentiment might lead to more rational and cautious trading, which then leads to a decrease in volatility. The theory and literature reviewed above is supported by empirical findings that show a positive relationship between investor sentiment and volatility (Yang & Copeland, 2014; Fang et al., 2018).

It becomes clear that theory and empirical findings show that volatility is higher in times of higher investor sentiment. However, does this automatically mean that investors just react more extreme to financial catalysators during times of higher investor sentiment? Simoes Vieira (2011) looks therefore at share price reaction after changes in dividend. It is found that when dividends increase in times of higher investor sentiment, the positive reaction of the share price is larger. On the other hand, the share price reaction to a decrease in dividends is smaller if investor sentiment is high. Additionally, Bouteska (2019) shows that when a company restates its past financial results, investor sentiment moderates the cumulative abnormal returns and thus reduces the negative effect that restating financial results has on the share price. From the findings of the research above, it turns out that investors do not just react more extreme to financial catalysators in times of higher investor sentiment. They really react more positively/less negatively to these events.

2.1.3 Investor attention

Another important phenomenon in behavioral finance is that individual investors are net buyers of stocks in the news, stocks experiencing high abnormal trading volume, and stocks with extreme one-day returns

(Barber & Odean, 2008). They hypothesize that many investors only consider stocks that have first caught their attention as attention is a scarce resource. Odean already proposed the idea that investors limit their search to stocks that have recently caught their attention. In this way, personal preferences only determine the choices after attention has determined the choice set. For example, a momentum investor will chase recent performers in their choice set determined by their attention. Claims about volume increases on days with information releases or large price moves have been documented before (Karpoff, 1987; Bamber, Barron and Stober, 1997; Seasholes & Wu, 2004). Merton's theory (1987) suggests that investors' attention could increase company valuations by alleviating potential informational frictions that prevent lesser-known stocks to be hold by investors. Both the predictions from Merton's theory (1987) and the theory of Barber and Odean (2008) hold that positive shock to investor attention for a certain asset should increase the valuation.

These predictions are amongst others tested by Fang and Peress (2009). They do so using firm-specific media coverage in the *New York Times*, *USA Today*, *Wall Street Journal* and *Washington Post* as a measure of investor attention in the period from 1993 to 2002. They find that companies without media coverage in the prior month earn 3% higher annualized returns in comparison with companies that had above-average media coverage. This percentage return can even be as high as 8-12% annualized for companies with low market capitalizations, high idiosyncratic volatility, high individual investor ownership and low analyst coverage. These results are in line with the predictions made above as companies that enjoy less investor attention should offer higher returns to compensate their owners for being imperfectly diversified (Tetlock, 2015). The same results are found when using different measures of investor attention, such as internet searches (Da et al., 2011), Super Bowl commercials (Fehle et al., 2005), CEO interviews on CNBC (Kim, 2011) and recommendations of CNBC's popular *Mad Money* show (Engelberg et al., 2012). The research done by Da et al. (2011), Kim (2011) and Engelberg et al. (2012) find evidence of partial reversal of the initial spike in stock prices, meaning that the increase in stock prices which is the result of an increase in investor attention will not be permanent. This is in line with the theory of slow-moving capital (Duffie, 2010). It becomes clear the mentioned academic literature that investor attention increases the demand and thus prices of an asset.

2.1.4 Investor attention, company names and tickers

Since investors' attention is limited and investors do not have the cognitive abilities to assess all stocks as potential investment options, they are likely to prefer stocks that have fluent, understandable names or tickers (Alter & Oppenheimer, 2006). Alter & Oppenheimer (2006) showed this both using an experimental survey and using an empirical study on IPO returns from pronounceable and unpronounceable tickers. Head et al. (2009) added to these findings by adding that tickers with a meaning and more fluent tickers outperformed the market by 11.5% on an annual basis. However, not all research has pointed in the same direction. Peterburgsky (2017) carries out an experiment similar to the experimental survey of Alter & Oppenheimer (2006) but his findings indicate that both for riskless and risky investments, individuals do not have a preference for pronounceable tickers. Moreover, individuals are not willing to pay more for the stocks with pronounceable tickers. Green & Jame (2012) also examine whether company names affect ownership, liquidity and higher valuations. They are the first to apply the Englishness algorithm by Travers & Olivier (1978) in finance. This measure of fluency is based on letter clusters and their frequency in the English language. Green & Jame (2012) find that short easy to pronounce names generally have broader company ownership, higher share turnover and lower transaction price impacts. Montone et al. (2023) later show that companies with more fluent names yield higher market-adjusted returns than companies with less fluent names and that this effect is concentrated among the smaller companies.

Two potential explanations for the fluency effect of a company name are that the company name contains information on the firms' quality, or the fluency works as an attention-grabbing characteristic (Montone et al., 2023). They find that outperformance of companies with fluent names is higher during times in which demand from noise traders is high. As these noise traders are assumed to be more prone to attention-grabbing biases, the latter of the two hypotheses is assumed to be true. This is further established by Fenneman et al. (2022). Durham & Santhanakrishnan (2016) show that stocks with the most fluent tickers result in lower returns in periods preceded by higher investor sentiment. They conclude that when speculation is high during times of higher investor sentiment, companies with fluent tickers get overinflated leading to lower returns in subsequent periods. It was already found by Itzkowitz & Itzkowitz (2017) that expert investors are relatively immune to name-based biases. They show this also by looking at alphabetical bias among tickers. Trading activity and liquidity is found to be higher for companies near the top of an alphabetical listing (Jacobs & Hillert, 2015; Itzkowitz et al., 2016). Altogether, it seems like there is enough academic evidence for tickers to have a significant impact on valuations and trading activity. An overview of the current academic literature on the effects of company names and stock tickers can be found in Table 1. Figure 1 shows a simple overview how ticker characteristics that generate more investor attention can result in higher valuations and trading activity, especially in times of higher investor sentiment.

Figure 1 Overview of the potential influence of ticker characteristics on valuations and trading activity

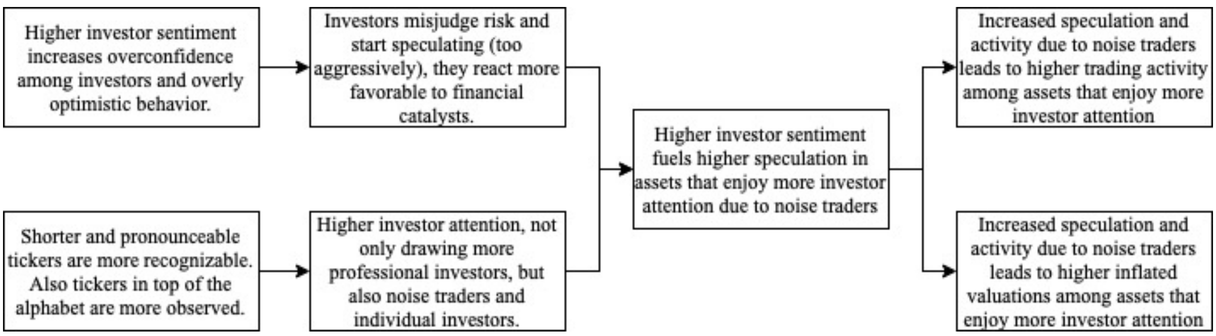


Table 1: Meta table of current academic literature on the effects of company names and stock tickers

Authors	Year	Subject	Comments/Findings
Alter & Oppenheimer	2006	Ticker pronounceability	Use case of IPO returns and find higher returns.
Head et al.	2009	Ticker meaning	Find outperformance of ticker with a meaning (e.g. LUV).
Green & Jame	2012	Company name fluency	Introduction fluency algorithm by Travers and Olivier (1978).
Jacobs & Hillert	2016	Alphabetical bias and trading activity	First to document alphabetical bias in financial markets.
Durham & Santhanakrishnan	2016	Ticker fluency	Use case of higher investor sentiment.
Itzkowitz & Itzkowitz	2017	Alphabetical bias and trading activity	Find that alphabetical bias also affects firm value.
Peterburgsky	2017	Ticker pronounceability	No effects of pronounceability in both risky and less risky assets.
Chan et al.	2018	Company name fluency	Effect on venture investment and IPO underpricing
Fang & Zhu	2019	Ticker complexity	Fewer holders, lower returns (also from IPOs) in Chinese market
Jin et al.	2021	Company name length and visibility premium	Find a premium for companies with three-character names
Fenneman et al.	2022	Company name fluency	Further prove that the fluency effect is a behavioral trait
Hsu et al.	2022	Company name fluency	Find that fluency positively effects acquisition premia
Montone et al.	2023	Company name fluency	More fluent name yields higher market-adjusted returns which are not due to the company names containing information on the quality of the firm.

2.2 Hypotheses

This research will focus on four different stock ticker characteristics. These are ticker length, whether a ticker is a real English word or not, pronounceability and alphabetical ranking. This might cause confusion as it is arguable that a real English word should also score higher on the pronounceability measure and the same might be true for shorter tickers. The current academic research mostly uses a measure based on the algorithm by Travers & Olivier (1978) that was among others also applied by Green and Jame (2012). In this algorithm, the "Englishness" of a word is assessed by the likelihood that the order of letters within a string will appear in English texts. Due to the construction of this measure of fluency, words generally seem to have a big advantage over tickers that are just as fluent but not a word. As a result, it makes sense to look at the different characteristics separately. It might be that the found fluency effect is actually just a pronounceability effect or the effect of a ticker being a word. Furthermore, due to the way the fluency measure used by Green & Jame (2012) is constructed, it does not necessarily consider the length of a ticker. However, the theory behind the found ticker effects is that easier and more recognizable tickers will attract more trading and a speculative premium (Durham & Santhanakrishnan (2016). Besides the pronounceability of a ticker and a ticker being a word, I also focus on alphabetical bias as evidence is found that alphabetical bias affects trading volume and firm valuations (Jacobs & Hillert, 2016; Itzkowitz & Itzkowitz, 2017). It is interesting to test if this alphabetical bias is also present in this case study using high investor sentiment as behavioral traits should be particularly clear due to amount of noise traders. Furthermore, the established research focusing on alphabetical bias has been focusing on company names and not yet on stock tickers. Lastly, I introduce a simple new ticker characteristic that might enjoy higher investor recognition: ticker length. The idea is that a shorter ticker is easier to remember than a longer ticker, which leads to higher investor recognition. Just as with all other ticker characteristics, higher investor recognition should lead to higher trading volume and higher asset prices due to a speculative premium.

Besides the ordinary effects of the four ticker characteristics to trading volume and asset valuations, I also perform additional tests to test whether the potential effects are more pronounced among smaller firms or bigger firms. This has also been done by Green & Jame (2013). Green & Jame argue that firms that investors are more often exposed to (read: bigger firms) increase the fluency of their otherwise nonfluent names. Applying this to tickers, this means that if an investor sees a ticker more often, he or she might find the ticker easier to pronounce than the first time he or she read it. Furthermore, Green & Jame (2013) argue that smaller companies have relatively high retail ownership. As individual investors are more susceptible to behavioral biases (Battalio & Mendenhall, 2005; Grinblatt & Keloharju, 2001), the effect should be more pronounced among smaller firms. Green & Jame (2013) show that the fluency effect is stronger among smaller firms. Applying all four of these characteristics to both trading activity and company valuations in eight separate testable hypotheses. In addition to these eight hypotheses, I propose that these effects are more pronounced for companies with a lower market capitalization.

Assuming that companies with a higher market capitalization are generally better known, they do not or to a lesser extent enjoy increased attention due to an easy-to-remember or easy findable stock ticker. As a result, I test the following sixteen hypotheses:

Hypothesis set 1:
1A: Companies with shorter stock tickers have higher trading volume than companies with longer stock tickers.
1B: Companies with stock tickers that also are an English word have higher trading volume than companies with less fluent stock tickers.
1C: Companies with stock tickers that are pronounceable have higher trading volume than companies with stock tickers that are not an English word.
1D: Companies with stock tickers that appear on the top of alphabetical listings have higher trading volume than companies with stock tickers that are lower in the alphabetical order.

Hypothesis set 2:
2A: The negative effect of ticker length on trading volume is more pronounced in smaller companies.
2B: The positive effect of a ticker being a word on trading volume is more pronounced in smaller companies.
2C: The positive effect of a ticker being pronounceable on trading volume is more pronounced in smaller companies.
2D: The positive effect of appearing on the top of alphabetical listings on trading volume is more pronounced in smaller companies.

Hypothesis set 3:
3A: Valuations of companies with shorter stock tickers have declined more than valuations of companies with longer stock tickers.
3B: Valuations of companies with stock tickers that also are an English word have declined more than valuations of companies with less fluent stock tickers.
3C: Valuations of companies with stock tickers that are pronounceable have declined more than valuations of companies with stock tickers that are not an English word.
3D: Valuations of companies with stock tickers that appear on the top of alphabetical listings have declined more than companies with stock tickers that are lower in the alphabetical order.

Hypothesis set 4:
4A: The negative effect of ticker length on change in market capitalization is more pronounced in smaller companies.
4B: The positive effect of a ticker being a word on change in market capitalization is more pronounced in smaller companies.
4C: The positive effect of a ticker being pronounceable on change in market capitalization is more pronounced in smaller companies.
4D: The positive effect of appearing on the top of alphabetical listings on change in market capitalization is more pronounced in smaller companies.

3 Data

This research uses a cross-sectional data set. In order to form the cross-sectional dataset, the data is retrieved from S&P Capital IQ. The measurement periods and moments have been formed based on investor sentiment data accessible on the webpage of Jeffrey Wurgler. This chapter covers the data sample, the different variables used and the data transformation.

3.1 Data sample

In their paper Durham & Santhanakrishnan (2016) show that stocks with the most fluent tickers result in lower returns in periods preceded by higher investor sentiment. They examine the underperformance during a period which started in times of high investor sentiment and ended in lower sentiment. During such a period higher inflated assets should also see higher deflation, resulting in the underpricing. This research aims to run similar test for the four identified stock ticker characteristics. The speculative times during and just after the pandemic recovery and the following bear market due to inflation and geopolitical events could provide an excellent case study. In order to identify the moments where the time frame should end, the Baker & Wurgler (2006) Sentiment Index is used. This index shows the sentiment in a certain month. The data is downloaded from https://pages.stern.nyu.edu/~jwurgler/, the NYU Stern webpage of Jeffrey Wurgler. Because I want to see how prices deflated for companies with certain ticker characteristics, I look for the highest and following lowest point. The moment in which investor sentiment was the highest was December 2021. The following lowest point is June 2022. The time frame for the research is thus December 2021 until June 2022. As the investor sentiment was already high in November 2021, I assume I can safely use the 1st of December as start date. June 2022 is the latest observation in the dataset so we don't know whether investor sentiment went up in the end of the month. As the investor sentiment is approximately just as low in May 2022 as in June 2022, it might be better to assume 1st of June as end date. The resulting specific timeframe is therefore December 1st 2021 until June 1st 2022.

Now that I have the time frame in which we will conduct this study on the effect of stock ticker characteristics, I can create the sample. A list of tickers from the New York Stock Exchange and Nasdaq are download through the database S&P CaptialIQ. CapitalIQ is a market intelligence data base by S&P that covers an extensive amount of company specific data and trading data. This list of stock tickers contains 3927 tickers. In order to generate a database with only real operating companies, special purpose acquisition companies (SPACs), real estate investment trusts (REITs) and closed-end funds are excluded from the dataset. Due to the special nature of these companies, they will not form a good comparison between the regular operating companies. They could very well be used in additional research on tickers (e.g. ticker characteristics and flows into closed-end funds) but that is not within the scope of this research. This results in a dataset of 3821 observations. One could argue that the inclusion of financials and utility companies could cause problems. Dummy variables are included for industry classification, including financials and utility companies, to avoid these categories causing problems.

3.2 Variables

3.2.1 Independent variables: Ticker Length, Ticker Word and Alphabetical bias

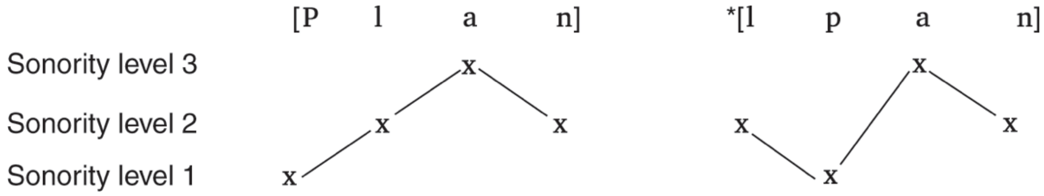
From the list of stock tickers, it becomes really easy to come up with three characteristics. For ticker length, Excel can count the letters in the ticker. Furthermore, to check whether a ticker is also a word in English the spell-checker in Microsoft word is used. Tickers that are also words will get a value of one and tickets that are not will get a value of 0. For generating a variable to test alphabetical bias, the tickers are alphabetically ordered and provided with observation id's. The observations are then divided into groups of the first 1%, 10%, 20% and 50%. In this way These intervals are not similar but assume that attention decreases the fastest in the beginning and is concentrated in the top. On a webpage, everyone sees instantly the first page of tickers, but this does not mean that everyone is also going to check the second page. On the other hand, if people checked 47/50 pages, chances are relatively higher that they are going to visit also the 48th page.

3.2.2 Independent variables: Ticker Pronounceability

To assess the tickers on their fluency is more of a challenge. The algorithm by Travers & Olivier (1978) was among others also applied by Green & Jame (2012) was presented as a good measure of fluency. In this algorithm, the "Englishness" of a word is assessed by the likelihood that the order of letters within a string will appear in English texts. However, the algorithm by Travers & Olivie has some drawbacks. First, the algorithm has mostly been applied to company names and not tickers. If you are going to check in the database of Corpus of Contemporary American English (COCA) how many times a string like "XTRX" will appear in English text, it will give an error while a word like "THE" will result in tens of millions of hits. Moreover, the measure used by Green and Jame (2012) is rather complex and requires lots of searches in the COCA database. Due to limited access to this database, it is not an option to carry out all these searches and calculation anyway.

In order to cope with this problem, I develop a measure of pronounceability. To understand how I did this, it is important to understand the structure of a syllable. A syllable can have three parts: the *onset*, the *nucleus* and the *coda*. The nucleus is commonly the vowel of a syllable and the onset and coda are the consonant clusters in front of and after the nucleus (Anderson et al., 2018). For example, in the word "class", the "cl" is the onset, the "a" is the nucleus and the "ss" is the coda. There are also words that do not have all three. For example, the word sea has an onset (s) and nucleus (ea) but does not have a coda. The measure of pronounceability is based on the presence of a nucleus and the pronounceability of the onset and the coda as mentioned in Essentials of Linguistics (Anderson, 2018). When a ticker does not have a nucleus, it is regarded as unpronounceable. Examples of such tickers could be "TKFS" or "DDRW". The next requirement for a pronounceable ticker is that the onset and coda of a ticker, if there are, are pronounceable. If one or both are missing, the ticker is still regarded as pronounceable. Examples to think of could be “ART”, “GREE” or just “EA”. It is harder to determine whether an onset or coda is pronounceable. To do so, I use the Sonority Sequence Principle. Sonority is the relative loudness of a sound in a cluster of letters. The nucleus is the peak in sonority within a syllable (Fasold & Connor-Linton, 2014). The Sonority Sequencing Principle then states that onsets must rise in sonority while codas must decline in sonority (Clements, 2009). As a result of this general rule, some onsets or codas can be regarded as not pronounceable. For example, “STR” could be a pronounceable onset (think of *strip*) but it cannot be a coda (think of *pistr*). It also works the other way around with a consonant cluster as “NG”, it does not work as onset (think of *ngark*) but it does work as coda (think of *ring*). See Figure 2 below for a clear example of the Sonority Sequencing Principle.

Figure 2: Illustration of the Sonority Sequencing Principle



In short, a ticker is thus regarded as pronounceable if it has a nucleus and the onset and coda are pronounceable or absent. If a ticker matches these conditions the ticker gets a value of 1 and if it does not it gets a value of 0. It is thus a binary variable. Although there are exceptions to this Sonority Sequencing Principal (Fasold & Connor-Linton, 2014), the criteria seem to perform fairly good. To show that this measure works quite well, some 20 tickers are provided below (Figure 3) together with their values.

Figure 3: Illustration of pronounceability using Sonority Sequencing Principle

GUG	1	BIRD	1	WAVC	0	SRAD	0
NMAI	0	SONX	1	XERS	1	RLYB	0
BRZE	0	FLNC	0	CION	1	RELY	1
IREN	1	INFA	1	ECAT	1	GXO	0
TCBX	0	PTLO	0	SLVM	0	ERAS	1

3.2.3 Dependent variables

Trading Volume

Trading volume is measured in December 2021. Based on the literature review the difference in investor attention should be bigger in times of higher investor sentiment. As a result, December 2021 is assumed to be the best period to examine the sought after effects. Trading volume is measured by adding up all daily trading volumes in millions in December and dividing it by the 22 trading days in December. As this number is small and for most companies has multiples zeros behind the comma, I multiply the number by 1.000. For in order to change these absolute trading volumes, the trading volumes are divided by the number of shares outstanding on the balance sheet. This number of shares outstanding is calculated by the total number of common shares outstanding. This value is calculate by Capital IQ based on the sum of all classes of common stock entitled to economic distributions. The amount of shares outstanding is retrieved as of December 1st 2021. This measure of trading volume seems to be highly skewed. Therefore, I will use the logarithm of the measure.

Change in Market Capitalization

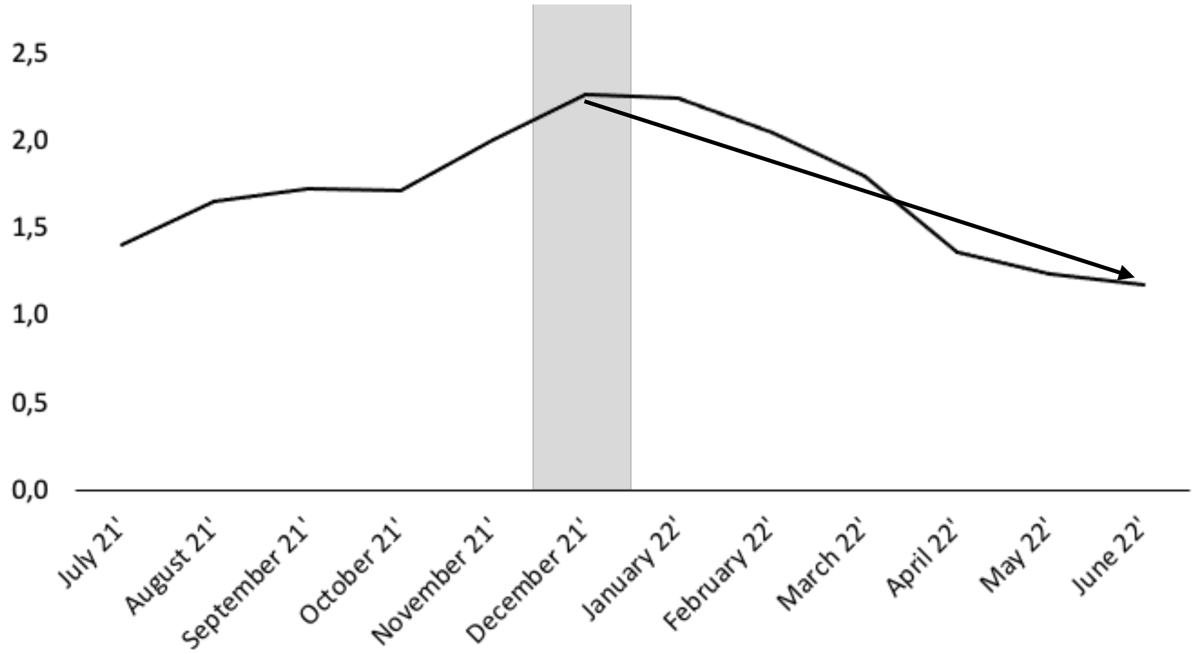
Returns are calculated as the percentage change in the market capitalization from December 1st 2021 to June 1st 2022. Using the market capitalization controls for certain corporate actions that affect stock prices but not the market capitalization, such as stock splits for example. The formula to compute the changes is:

$$\Delta MC = \frac{MC_{t=1} - MC_{t=0}}{MC_{t=0}}$$

Where $MC_{t=0}$ represents the market capitalization at the 1st of December 2021 and $MC_{t=1}$ represents the market capitalization at the 1st of June 2022. As the change in market capitalization is calculated over the period as a whole, the data is solely cross-sectional.

Figure 4: **Illustration of sample periods**

Visual representation of the used month for the trading volume and the period of which the changes in market capitalization have been calculated. The line represents the Baker & Wurgler sentiment index.



Note. The grey area represents the period of which the average daily trading volumes relative to the outstanding shares are calculated after which the logarithm of the relative average daily trading volume of December 2021 is used as dependent variable.

The black arrow indicates the fall in investor sentiment from December 1st 2021 to June 1st which is used as period over which the changes in market capitalization are calculated.

3.2.4 Control variables

Percentage afloat

Not all outstanding shares are openly traded on exchanges. Sometimes there are closely held shares that are held by insiders or controlling investors. For companies that have a lot of its shares hold by insiders, the percentage of shares traded divided by the total outstanding shares will be higher than for its counterpart that has relatively limited insider holdings. Moreover, public companies can still have big funds as equity holder who have shares that are closely hold and not openly traded. It is important to keep these holdings in mind as well. The percentage afloat is calculated as the number of floating shares divided by the number of outstanding shares and is measured as of December 1st 2021. The floating shares is established in many academic papers among multiple stock markets (Bostanci & Kiliç, 2010; El Nader, 2018; Liao et al., 2022; Hasnawati et al., 2022). As the trading volume is measured relative to the number of outstanding shares. Therefore, I also use the relative measure for floating shares, being the percentage afloat.

Firm size

As I want to find the pure effect of the tickers, it is important to control for firm size. As bigger companies in general will attract more investor attention, they might end up with higher trading volume and valuations just because they are bigger. Furthermore, bigger companies can typically be better and more analyzed by analysts and have a bigger investor base. As there can be more information available about the bigger companies and they are more analyzed, there might be less room for noise trading since mispricing will be lower and will be corrected faster. There are multiple usable measures for firm size are applicable in different scenarios and research goals (Dang et al., 2018). In this research I will use two common measures for firm size. The problem of a firm size measure that it is they are often either backward-looking or forward-looking. Therefore, I will include two measures that capture both the backward-looking and forward-looking aspects: sales (backward-looking) and enterprise value (forward-looking). Sales is measured as the sales in Financial Year 2021 and market capitalization is measured at the beginning of the research timeframe, being December 1st 2021.

Market-to-book ratio

In addition to a forward-looking measure for firm size, I also include a market-to-book (M/B) ratio as a kind of valuation measure. It is a metric that compares the market capitalization of a company to the book value in which the book value is the total value of the equity on the balance sheet. A high market-to-book value is generally interpreted as a positive signal as it generally indicates future growth and financial stability. Studies by Fama & French (1992) found that companies with lower market-to-book ratios tend to underperform companies with higher market to book values. The market-to-book ratio is measures at the beginning of the research timeframe, being December 1st 2021. While inspecting the data, it showed that the market-to-book ratios were highly skewed. For this reason, I use the log of the market-to-book ratios.

Debt-to-equity ratio

The debt-to-equity ratio is a measure of the leverage of a company and is calculated by dividing the firm's total liabilities by its shareholder's equity. The ratio indicates the firms use of debt to finance its operations and assets (Kim, 2018). If a company has a lot of debt, it can be a big company while having not as big of a market capitalization. If still a lot of investors want to buy or sell shares in this bigger company, the relative number of shares traded might be higher for companies with relatively much debt. Therefore, the debt-to-equity ratio is included in the tests trying to examine a potential relationship between ticker characteristics and trading volume.

In addition to the tests focusing on trading volume, the debt-to-equity is also useful in the test focusing on company valuations. As the company has a certain interest burden as a result of the debt, return for equity will be less for companies that barely have a positive return due to this interest burden. On the other hand, if a company with a lot of debt can easily pay its interest and makes healthy profits, the return on equity will be higher. As a result, risk in companies is higher for companies with relatively high leverage. Therefore, leverage is an important determinant in valuations and is important to consider. The debt-to-equity ratio is measures at the beginning of the research timeframe, being December 1st 2021. While inspecting the data, it showed that the debt-to-equity ratios were highly skewed. For this reason, I use the log of the debt-to-equity ratios.

Industry dummies
In order to control for industry effects, I use the primary industry classification used by CapitalIQ. The 11 distinguished industries are: energy, materials, industrials, consumer discretrionary, consumer staples, healthcare, financials, information technology, communication services, utilities and real estate. In order to control for this classification, I create industry dummies based on the classification. These industry dummies are used in both the test on trading volume and the stock returns.

3.3 Data transformation and descriptive statistics
Figure 3 provides a table with the descriptive statistics of the sample of the independent, dependent and control variables. Since not all variables are available for every company in the main dataset, the dataset is reduced to observations for which all control variables can be generated using the S&P CapitalIQ database. As we use different control variables in the tests for trading volume and change in market capitalization, this generates two different datasets. The dataset used for the test on trading volume has 2017 observations and will be referred to as dataset A. The dataset for the tests on change in market capitalization has 2019 observations and will be referred to as dataset B. This difference in number of observations is due to the fact that for two of companies there was no data on the percentage afloat. I realize that this is a big cut in the number of observations, however having not all information could lead to biases. Therefore, I prefer quality over quantity.

In order cope with extreme outliers in the variables market-to-book ratio and debt-to-equity ratio that could strongly influence the results of the performed tests, these variables are winsorized at the 1% and 99% levels. This is done separately for each dataset to make sure that in both the variables are really winsorized at the 1% and 99% levels. In addition to these control variables, the change in market capitalization also suffered from severe outliers. Therefore, the change in market capitalization was winsorized as well. The summary statistics of both dataset A and dataset B can be found in Table 2A.

Table 2A: Summary statistics dataset A and dataset B

	A: Trading Volume N=2017			B: Change in Market Cap N=2019		
	Mean	Median	Std. Dev	Mean	Median	Std. Dev
Ticker Length	3.46	4	0.67	3.46	4	0.67
Ticker Word	0.18	0	0.38	0.18	0	0.38
Ticker Pronounceability	0.31	0	0.46	0.31	0	0.46
Alphabetical 1%	0.01	0	0.10	0.01	0	0.10
Alphabetical 5%	0.05	0	0.22	0.05	0	0.22
Alphabetical 10%	0.10	0	0.30	0.10	0	0.30
Alphabetical 20%	0.20	0	0.40	0.20	0	0.40
Alphabetical 50%	0.50	0	0.50	0.50	0	0.50
LogTradingVolume[1]	1.89	1.87	0.73	1.89	1.87	0.73
Change in Market Cap[1]	-10.05	-12.09	35.48	-10.02	-12.09	35.50
Percentage Afloat[2]	82.51	92.45	22.26	82.49	92.45	22.28
LogMarketCap[2]	8.34	8.26	1.69	8.34	8.26	1.69
LogSales	7.35	7.36	1.88	7.35	7.36	1.88
LogDebt/Equity ratio	4.07	4.29	1.45	4.07	4.29	1.45
LogMarket/Book ratio	1.32	1.14	0.91	1.32	1.14	0.91

Note.

1: Dependent variables; in the tests on trading volume, the variable change in market capitalization is not used and vice versa.

2: Control variables percentage afloat and the logarithm of the market capitalization are not used in the tests on change in market capitalization. In the observation selection for dataset B, it is not considered whether there was data for percentage afloat or logarithm of the market capitalization. As a result, the summary statistics for these variables might be affected by absence of data.

Table 2A contains the correlations between the different variables in dataset A. Based on Moore et al. (2013) a relationship is strong for $|R| > 0.7$, moderate for $0.5 < |R| < 0.7$, weak for $0.3 < |R| < 0.5$ and there is a very weak to no relationship when $|R| < 0.3$ where R denotes the correlation coefficient. Therefore, it is found that in general the correlations between all variables are very low. There is only one exception being the correlation between LogMarketCap and LogSales (0.72). This is in line with what could be expected as both are included as a proxy of size, one being backward-looking (LogSales) and one being forward looking (LogMarketCap). This means that one should be careful when including both LogMarketCap and LogSales as this could lead to multicollinearity. Potential multicollinearity could lead to overfitting problems and might make the model harder to interpret. As there are just two additional observations in dataset B, the correlations are assumed to be not significantly different.

Table 2B: Correlation table dataset A.

	1.	2.	3.	4.	5.	6.	7.	8.	9.	10.	11.
1.	1										
2.	-0.20	1									
3.	-0.06	0.41	1								
4.	0.03	-0.02	0.06	1							
5.	-0.01	0.05	0.03	0.01	1						
6.	-0.19	-0.04	0.00	0.02	-0.12	1					
7.	-0.12	0.01	0.02	0.02	0.27	0.15	1				
8.	-0.22	0.07	0.01	0.01	0.02	0.00	0.25	1			
9.	-0.30	0.04	0.01	0.01	0.01	0.25	0.28	0.72	1		
10.	-0.21	0.03	-0.01	0.00	0.03	0.18	0.11	0.13	0.36	1	
11.	0.06	0.05	-0.01	-0.03	0.06	-0.28	-0.03	0.40	0.06	0.19	1

Note. The table above shows the correlations between the used variables from dataset A, the dataset used for tests on trading volume. Due to lack of space, the number correspond with variables: 1. Ticker Length, 2. Ticker Word, 3. Pronounceability, 4. Alphabetical 50%, 5. Trading Volume, 6. Change in Market Cap, 7. Percentage Afloat, 8. LogMarketCap, 9. LogSales, 10. LogDebt/Equity ratio, 11. LogMarket/Book ratio.

4 Methodology

The main goal of this research is examining potential relationships between certain stock ticker characteristics and trading volume and company valuations. To do so, I use regular OLS regression incorporating the independent variables and control variables. As I use two-sided T-test, the critical p-value is 0.05. To carry out the test I use the statistical software Stata/MP 15.0.

4.1 Ticker characteristics and trading volume

In the hypothesis set 1, I focus on the potential relationship between stock ticker characteristics and trading volume. Based on the discussed literature in Chapter 2 it is hypothesized that stock tickers with certain characteristics might attract more investor attention and therefore have a higher trading volume. The ticker characteristics that are tested in this hypothesis set are ticker length, whether the ticker is an English word, pronounceability and alphabetical bias. Therefore, the first set of hypotheses is:

1A: Companies with shorter stock tickers have higher trading volume than companies with longer stock tickers.
1B: Companies with stock tickers that also are an English word have higher trading volume than companies with less fluent stock tickers.
1C: Companies with stock tickers that are pronounceable have higher trading volume than companies with stock tickers that are not an English word.
1D: Companies with stock tickers that appear on the top of alphabetical listings have higher trading volume than companies with stock tickers that are lower in the alphabetical order.

The effects of all these ticker characteristics are studied first separately and later are all combined in one regression using regular OLS regressions. In the regressions, the logarithm of the firm size and dummy variables for the Fama French 12 industry classification are included as control variables. As a result, the full regression equation (1) looks as follows:

$$
\begin{aligned}
(1)\ LogTradingVolume_i \\
&= \beta_0 + \beta_1 * Ticker\ Length_i + \beta_2 * Ticker\ Word_i + \beta_3 \\
&* Ticker\ Pronounceability_i + \beta_4 * Alphabetical\ 1\% + \beta_5 * Alphabetical\ 5\% \\
&+ \beta_6 * Alphabetical\ 10\% + \beta_7 * Alphabetical\ 20\% + \beta_8 * Alphabetical\ 50\% \\
&+ \beta_9 * Percentage\ Afloat_i + \beta_{10} * LogMarketCap + \beta_{11} * LogSales + \beta_{12} \\
&* LogDebt/Equity\ ratio_i + \beta_{13} * LogMarket/Book\ ratio_i + \delta I_i + u_i
\end{aligned}
$$

In the regression equation above, β_0 denotes the constant. β_1, β_2 and β_3 denote the effects of three of the independent variables respectively: ticker length, whether the ticker represents an English word, and whether the ticker is pronounceable. The alphabetical groups are represented by β_4, β_5, β_6, β_7 and β_8. So, β_1, β_2, β_3, β_4, β_5, β_6, β_7 and β_8 are the coefficients of interest. As it is expected that shorter tickers enjoy more investor attention, a negative coefficient is expected for β_1. Furthermore, it is hypothesized that a ticker being a word generates more investor attention. So, a positive coefficient is expected for β_2. The same holds for pronounceable tickers. It is expected that pronounceable tickers generate more investor attention. Therefore, also a positive coefficient is expected for β_3. Lastly, it is hypothesized that tickers among the top of alphabetical listings generate more investor attention, and thus trading volume. Therefore, it is also expected that some positive coefficients are found for being in the alphabetical top 1%, 5%, 10%, 20% or 50%.

β_9, β_{10}, β_{11}, β_{12} and β_{13} denote the effects of the control variables: percentage afloat, sales, market capitalization, market-to-book ratio, debt-to-equity ratio respectively. As is usually done in empirical corporate finance, I use the log of the variables representing firm size: sales and market capitalization. δ denotes the vector of effects of the industry classifications that are represented by I. While performing the first tests on changes in market capitalization, I used conducted Brausch-Pagan tests using different ticker characteristics in order to test for heteroskedasticity. In all test, the null-hypothesis was rejected, confirming the presence of heteroskedasticity. In order to cope with this heteroskedasticity, I use robust standard errors, also known as Huber-White standard errors. u_i denotes the error term of an observation. When examining the effects found using the tests, an effect is found to be significant if the corresponding p-value is below the 0.05 significance level as formulated and proposed by Pesaran et al. (2001). In the results section corresponding to this hypothesis set, the results are discussed and the hypotheses are rejected if effects are found to be insignificant. The regression is performed five times: once for each independent variable, and once including all independent variables.

As noted in Chapter 2, it might be the case that the attention effects of some of the ticker characteristics might only hold for small firms as bigger firms already enjoy enough investor attention. In this case, the bigger firms are assumed to be already well-known to the extent that investors do not or less need easy-to-remember tickers to remember or find the firm. As a result, we should see higher trading volumes among firms with tickers that should generate more investor attention. The hypotheses that correspond with this reasoning are:

2A: The negative effect of ticker length on trading volume is more pronounced in smaller companies.
2B: The positive effect of a ticker being a word on trading volume is more pronounced in smaller companies.
2C: The positive effect of a ticker being pronounceable on trading volume is more pronounced in smaller companies.
2D: The positive effect of appearing on the top of alphabetical listings on trading volume is more pronounced in smaller companies.

To examine these potential effects, companies are ranked based on their market capitalization and distributed in quintiles. The first Size Quintile (SQ1) contains the top 20% biggest firms based on the market capitalizations and the fifth Size Quintile (SQ5) contains the 20% smallest firms based on the market capitalizations. The rest of the variables are kept as they were in regression equation (1). This results in the following full regression equation (2):

$$
\begin{aligned}
(2)\ LogTradingVolume_i &= \beta_0 + \beta_{13} * SQy + \beta_1 * Ticker\ Length_i + \beta_{14} * (Ticker\ Length_i * SQy) + \beta_2 \\
&* Ticker\ Word_i + \beta_{15} * (Ticker\ Word_i * SQy) + \beta_3 * Ticker\ Pronounceability_i \\
&+ \beta_{16} * (Ticker\ Pronounceability_i * SQy) + \beta_4 * Alphabetical\ 1\% + \beta_{17} \\
&* (Alphabetical\ 1\% * SQy) + \beta_5 * Alphabetical\ 5\% + \beta_{18} * (Alphabetical\ 5\% \\
&* SQy) + \beta_6 * Alphabetical\ 10\% + \beta_{19} * (Alphabetical\ 10\% * SQy) + \beta_7 \\
&* Alphabetical\ 20\% + \beta_{20} * (Alphabetical\ 20\% * SQy) + \beta_8 \\
&* Alphabetical\ 50\% + \beta_{21} * (Alphabetical\ 50\% * SQy) + \beta_9 \\
&* Percentage\ Afloat_i * SQy + \beta_{10} * LogSales + \beta_{11} \\
&* LogDebt/Equity\ ratio_i + \beta_{12} * LogMarket/Book\ ratio_i + \delta I_i + u_i
\end{aligned}
$$

In the regression (2), β_{13} is added which represents the effect of the Size Quintiles (y). Once again β_0 denotes the constant. β_1, β_2 and β_3 denote the effects of three of the independent variables respectively: ticker length, whether the ticker represents an English word, and whether the ticker is pronounceable. The alphabetical groups are represented by β_4, β_5, β_6, β_7 and β_8.

In regression equation (2) the coefficients of interest are β_{14}, β_{15}, β_{16}, β_{17}, β_{18}, β_{19}, β_{20} and β_{21}. β_{14}, β_{15} and β_{16} denote the interaction effects of the Size Quintiles and ticker length, whether the ticker represents an English word and whether the ticker is pronounceable. β_{17}, β_{18}, β_{19}, β_{20} and β_{21} represent the interaction effects of the Size Quintiles and the alphabetical groups, being 1%, 5%, 10%, 20% and 50%.

β_9, β_{10}, β_{11} and β_{12} denote the effects of the control variables: percentage afloat, sales, market-to-book ratio, debt-to-equity ratio respectively. Market capitalization is left out as the automatic inclusion of the Size Quintiles makes the inclusion of the original variable unnecessary. As is usually done in empirical corporate finance, I use the log of the variables representing firm size: sales and market capitalization. δ denotes the vector of effects of the industry classifications that are represented by I. u_i denotes the error term of an observation. In the tests focusing on potential interaction effect of ticker characteristics and firm size, I also use robust standard errors. When examining the effects found using the tests, an effect is found to be significant if the corresponding p-value is below the 0.05 significance level as formulated and proposed by Pesaran et al. (2001). In the results section corresponding to this hypothesis set, the results are discussed and the hypotheses are rejected if effects are found to be insignificant. The regression is performed five times: once for each independent variable, and once including all independent variables.

The interaction effects are examined only individually as the inclusion of all interaction effects, would lead to an overload of input variables which could potentially lead to overfitting. In case of overfitting, the model appears to work really well but this can be mainly due to a big number of variables in model instead of actual predicting/describing power of the model.

4.2 Ticker characteristics and change in market capitalization

The second set of hypotheses focusses on the potential relationship between stock ticker characteristics and company valuations. Based on the discussed literature in Chapter 2 it is hypothesized that stock tickers with certain characteristics might attract more investor attention and therefore have a higher valuation. In order to quantify differences in company valuations, this research is based on the idea that valuations are inflated during times of higher investor sentiment. Companies that attract more investor attention through their ticker could therefore have more heavily inflated stock prices that companies with less attention-grabbing tickers. As a result, it is expected that tickers that have less letters, are an English word, are pronounceable or are higher in the alphabetical order lead to more heavily deflation when investor sentiment cools down. The returns of the assets corresponding with these kinds of tickers should have therefore lower returns. Hypothesis set 3 is based on this reasoning and contains the following hypotheses:

3A: Valuations of companies with shorter stock tickers have declined more than valuations of companies with longer stock tickers.
3B: Valuations of companies with stock tickers that also are an English word have declined more than valuations of companies with less fluent stock tickers.
3C: Valuations of companies with stock tickers that are pronounceable have declined more than valuations of companies with stock tickers that are not an English word.
3D: Valuations of companies with stock tickers that appear on the top of alphabetical listings have declined more than companies with stock tickers that are lower in the alphabetical order.

The potential effects of all these ticker characteristics are studied first separately and later are all combined in one regression using regular OLS regressions. In the regressions, the logarithm of the firm size and dummy variables for the Fama French 12 industry classification are included as control variables. As a result, the full regression equation (3) looks as follows:

$$(3)\ Change\ in\ Market\ Capitalization \\ = \beta_0 + \beta_1 * Ticker\ Length_i + \beta_2 * Ticker\ Word_i + \beta_3 \\ * Ticker\ Pronounceability_i + \beta_4 * Alphabetical\ 1\% + \beta_5 * Alphabetical\ 5\% \\ + \beta_6 * Alphabetical\ 10\% + \beta_7 * Alphabetical\ 20\% + \beta_8 * Alphabetical\ 50\% \\ + \beta_9 * LogSales + \beta_{10} * LogDebt/Equity\ ratio_i + \beta_{11} \\ * LogMarket/Book\ ratio_i + \delta I_i + u_i$$

In the regression equation above, β_0 denotes the constant. β_1, β_2 and β_3 denote the effects of three of the independent variables respectively: ticker length, whether the ticker represents an English word, and whether the ticker is pronounceable. The alphabetical groups are represented by β_4, β_5, β_6, β_7 and β_8. So, β_1, β_2, β_3, β_4, β_5, β_6, β_7 and β_8 are the coefficients of interest. As it is expected that shorter tickers enjoy more investor attention, a negative coefficient is expected for β_1. Furthermore, it is hypothesized that a ticker being a word generates more investor attention. So, a negative coefficient is expected for β_2. The same holds for pronounceable tickers. It is expected that pronounceable tickers generate more investor attention. Therefore, also a negative coefficient is expected for β_3. Lastly, it is hypothesized that tickers among the top of alphabetical listings generate more investor attention, and thus should have declined more heavily. Therefore, it is also expected that some negative coefficients are found for being in the alphabetical top 1%, 5%, 10%, 20% or 50%.

β_9, β_{10} and β_{11} denote the effects of the control variables: sales, market-to-book ratio, debt-to-equity ratio respectively. I use the log of sales, just as in the test on trading volume. δ denotes the vector of effects of the industry classifications that are represented by I. u_i denotes the error term of an observation. While performing the first tests on changes in market capitalization, I used conducted Brausch-Pagan tests using different ticker characteristics in order to test for heteroskedasticity. In all test, the null hypothesis was rejected, confirming the presence of heteroskedasticity. In order to cope with this heteroskedasticity, I use robust standard errors, also known as Huber-White standard errors. When examining the effects found using the tests, an effect is found to be significant if the corresponding p-value is below the 0.05 significance level as formulated and proposed by Pesaran et al. (2001). In the results section corresponding to this hypothesis set, the results are discussed and the hypotheses are rejected if effects are found to be insignificant. The regression is performed five times: once for each independent variable, and once including all independent variables.

As is also done in the test focusing on the potential effect of the ticker characteristics on trading volume, the potential interaction effects of the ticker characteristics and the Size Quintiles on the change in market capitalization are tested. As noted in Chapter 2, it might be the case that the attention effects of some of the ticker characteristics might only hold for small firms as bigger firms already enjoy enough investor attention. In this case, the bigger firms are assumed to be already well-known to the extent that investors do not or less need easy-to-remember tickers to remember or find the firm. Therefore, the effects of tickers should be more pronounced among smaller firms. This leads to the following four hypotheses of hypothesis set 4:

4A: The negative effect of ticker length on change in market capitalization is more pronounced in smaller companies.
4B: The positive effect of a ticker being a word on change in market capitalization is more pronounced in smaller companies.
4C: The positive effect of a ticker being pronounceable on change in market capitalization is more pronounced in smaller companies.
4D: The positive effect of appearing on the top of alphabetical listings on change in market capitalization is more pronounced in smaller companies.

To test whether the effects of ticker characteristics are indeed stronger for smaller companies, the interaction effects and the effect of the Size Quintiles are added to the regression equation. The rest of the variables are kept as they were in regression equation (3). This results in the following full regression equation (4):

$$
\begin{aligned}
(4)\ & Change\ in\ Market\ Capitalization \\
& = \beta_0 + \beta_{12} * SQy + \beta_1 * Ticker\ Length_i + \beta_{13} * (Ticker\ Length_i * SQy) + \beta_2 \\
& * Ticker\ Word_i + \beta_{14} * (Ticker\ Word_i * SQy) + \beta_3 * Ticker\ Pronounceability_i \\
& + \beta_{15} * (Ticker\ Pronounceability_i * SQy) + \beta_4 * Alphabetical\ 1\% + \beta_{16} \\
& * (Alphabetical\ 1\% * SQy) + \beta_5 * Alphabetical\ 5\% + \beta_{17} \\
& * (Alphabetical\ 5\% * SQy) + \beta_6 * Alphabetical\ 10\% + \beta_{18} \\
& * (Alphabetical\ 10\% * SQy) + \beta_7 * Alphabetical\ 20\% + \beta_{19} \\
& * (Alphabetical\ 20\% * SQy) + \beta_8 * Alphabetical\ 50\% + \beta_{20} \\
& * (Alphabetical\ 50\% * SQy) + \beta_9 * LogSales + \beta_{10} \\
& * LogDebt/Equity\ ratio_i + \beta_{11} * LogMarket/Book\ ratio_i + \delta I_i + u_i
\end{aligned}
$$

In the regression (4), β_{12} is added which represents the effect of the Size Quintile used in the specific test. Once again β_0 denotes the constant. β_1, β_2 and β_3 denote the effects of three of the independent variables respectively: ticker length, whether the ticker represents an English word, and whether the ticker is pronounceable. The alphabetical groups are represented by β_4, β_5, β_6, β_7 and β_8.

In regression equation (4) the coefficients of interest are β_{13}, β_{14}, β_{15}, β_{16}, β_{17}, β_{18}, β_{19} and β_{20}. β_{13}, β_{14} and β_{15} denote the interaction effects of the Size Quintiles and ticker length, whether the ticker represents an English word and whether the ticker is pronounceable. β_{16}, β_{17}, β_{18}, β_{19} and β_{20} represent the interaction effects of the Size Quintiles and the alphabetical groups, being 1%, 5%, 10%, 20% and 50%.

β_9, β_{10} and β_{11} denote the effects of the control variables: sales, market-to-book ratio, debt-to-equity ratio respectively. δ denotes the vector of effects of the industry classifications that are represented by I. u_i denotes the error term of an observation. In the tests focusing on potential interaction effect of ticker characteristics and firm size, I also use robust standard errors. When examining the effects found using the tests, an effect is found to be significant if the corresponding p-value is below the 0.05 significance level as formulated and proposed by Pesaran et al. (2001). In the results section corresponding to this hypothesis set, the results are discussed and the hypotheses are rejected if effects are found to be insignificant. The regression is performed five times: once for each independent variable, and once including all independent variables.

The interaction effects are examined only individually as the inclusion of all interaction effects, would lead to an overload of input variables which could potentially lead to overfitting. In case of overfitting, the model appears to work really well but this can be mainly due to a big number of variables in model instead of actual predicting/describing power of the model.

5 Results

In this chapter I present the results from the different performed OLS regressions and mixed effects regressions. The outcomes of the regressions are presented in clear tables, accompanied by brief discussions on whether the hypotheses are rejected or not. Finally, the chapter ends with a table presenting the main findings in one overview.

5.1 Ticker characteristics and trading volume

5.1.1 HS1: Ticker characteristics and trading volume: simple OLS regressions

In Table 3 the results from regression equation 1 are quantified. This includes the four separate regressions for each ticker characteristic and one regression including all ticker characteristics. The results illustrate the relationships between the ticker characteristics and trading volume. Furthermore, the control variables are included in all regressions. This means that also the dummy variables for the industry classifications are included in the model.

Observations from the test outputs

While performing the tests, Stata by itself omitted the industry classification 'Communication Services' due to collinearity. This could mean that there is another highly correlated independent variable included in the model. Unfortunately, Stata does not show what the variable is that is highly correlated to the industry classification 'Communication Services'. Another reason why the binary variable for 'Communication Services' has been left out is because there has to be a base effect for the industries. The other industry effects are then relative to this base effect. Most of the dummy variables for the industry classifications are found to be highly significant in every performed test. Industries that generally have less of a significant effect are 'Information Technology' and 'Consumer Staples'. The rest of the dummy variables have a significant negative effect, except for 'Consumer Discretionary'. The coefficients of the industry dummies all range between -1 and 1. Furthermore, in the data section it was said that one should be careful when interpreting the coefficients for firm size measures. The effect of firm size seems to be completely absorbed by the variable LogSales as it is highly significant in every test while LogMarketCap is not found be significant at all. Remarkably, both the logarithm of the debt-to-equity ratio and the logarithm of the market-to-book ratio are found to be insignificant at any significance level. Lastly, the F-statistic is relatively high and highly significant for all models, while differing somewhat per model. The R^2 of all models is between the 0.17 and 0.18, meaning that about 17% to 18% of the variation in the dependent variable is explained by the model. This seems to be relatively low. One potential explanation for this could be that trading volume is very dependent on firm specific news. Unfortunately, such a variable is not included in the model. Identifying and measuring firm specific news can be very complex and hard to implement.

Ticker length has negative effect on trading volume, in line with the hypothesis based on academic research. However, this effect is insignificant at the 10% significance level in both the test using solely ticker length and the test using all ticker characteristics at the same time. In general, the ticker pronounceability and alphabetical ranking seem to have no effect on the trading volume. Whether the ticker is an English word does seem to have some positive effect on trading volume, which is in line with the hypothesis based on the literature. The effect is statistically significant at the 10% significance level when tested separately but is not significant in the regression using all independent variables. The effect seems therefore to be very weak. Hence, it might be too early to draw conclusion solely based on these test outputs. Percentage afloat and the logarithm of the sales seem to have a strong positive and strong negative effect respectively throughout all performed regressions, some even at the 1% significance level. It makes sense that the trading volume is higher if there are more shares afloat. However, the fact that trading volume seems to be declining in sales can be somewhat surprising. One might expect bigger companies to enjoy more investor attention and therefore more relative trading volume. However, it seems like the opposite is true.

Implications for the hypotheses

In the first set of hypotheses, the main underlying hypothesis is that more recognizable ticker and tickers that are easier to remember or find have higher trading volume. The first subhypothesis (1A) states that companies with tickers that contain less letters generally have higher trading volume. This means that a significant negative effect should have been found for the variable Ticker Length. In the first performed regression focusing on this Ticker Length a negative effect of -0.0404 was found. However, this effect is found to be insignificant. In the regression that includes all ticker characteristics looked at, no significant coefficient was found either. Following the results from the first set of performed regressions, it becomes clear that in general the number of letters in a ticker does not affect trading volume. As a result, hypothesis 1A is rejected.

The second subhypothesis of the first hypothesis set (1B) states that companies with tickers that resemble an English word generally have higher trading volume. This means that a significant positive effect should have been found for the variable Ticker Length. In the first performed regression focusing on this Ticker Word a positive effect of 0.0731 was found. This effect is found to be significant at the 10% significance level but not at the 5% significance level. In the regression that includes all ticker characteristics looked at, no significant coefficient was found either. Following the results from the first set of performed regressions, it becomes clear that in general trading volume is not higher for firms which have a ticker that resembles an English word. As a result, hypothesis 1B is rejected.

The third subhypothesis of the first hypothesis set (1C) states that companies with tickers that are pronounceable generally have higher trading volume. This means that a significant positive effect should have been found for the variable Ticker Pronounceability. In the first performed regression focusing on this Ticker Pronounceability a positive effect of 0.053 was found. However, this effect is found to be insignificant at any significance level. In the regression that includes all ticker characteristics looked at, no significant coefficient was found either. Following the results from the first set of performed regressions, it becomes clear that in general trading volume is not higher for firms which have a pronounceable ticker. As a result, hypothesis 1C is rejected.

The last hypothesis that is not focused on interaction effects in hypothesis set 1 (1D) states that tickers that are higher in the alphabetical order have higher trading volume than companies with stock tickers that are lower in the alphabetical order. This means that a significant positive effect should have been found for the variables Alphabetical *X*%. In both the regression focusing solely on the alphabetical bias and the regression that uses all ticker characteristics, none of the alphabetical groups seem to have any significant effect on trading volume. Following the results from the first set of performed regressions, there seems to be no alphabetical bias at all. Therefore, hypothesis 1D is rejected. In addition to these simple OLS regressions, regressions with an interaction effect of the firm characteristics and firm size will be performed next. These additional tests will examine whether the alphabetical bias found by Jacobs and Hillert (2015) and Itzkowitz et al. (2016) is also present in dataset A.

Table 3: Regression output for ticker characteristics and trading volume.

	(1)	(2)	(3)	(4)	(5)
Ticker Length	-0.0404				-0.0345
	(0.0268)				(0.0274)
Ticker Word		0.0731*			0.0548
		(0.0390)			(0.0433)
Pronounceability			0.0353		0.0144
			(0.0323)		(0.0356)
Alphabetical 1%				-0.0600	-0.0637
				(0.1859)	(0.1832)
Alphabetical 5%				-0.0996	-0.1071
				(0.0947)	(0.0947)
Alphabetical 10%				0.0192	0.0301
				(0.0794)	(0.0806)
Alphabetical 20%				0.0148	0.0127
				(0.0574)	(0.0576)
Alphabetical 50%				0.0102	0.0111
				(0.0341)	(0.0342)
Percentage Afloat	0.0111***	0.0111***	0.0111***	0.0111***	0.0110***
	(0.0009)	(0.0009)	(0.0009)	(0.0009)	(0.0009)
LogMarketCap	0.0068	0.0075	0.0088	0.0103	0.0070
	(0.0198)	(0.0197)	(0.0197)	(0.0198)	(0.0200)
LogSales	-0.0509***	-0.0479**	-0.0486**	-0.0492***	-0.0500***
	(0.0192)	(0.0191)	(0.0191)	(0.0191)	(0.0192)
LogDebt/Equity ratio	0.0123	0.0143	0.0145	0.0144	0.0127
	(0.0141)	(0.0139)	(0.0139)	(0.0139)	(0.0141)
LogMarket/Book ratio	0.0166	0.0130	0.0141	0.0136	0.0151
	(0.0227)	(0.0227)	(0.0227)	(0.0228)	(0.0229)
Constant	1.5050***	1.3119***	1.3026***	1.3043***	1.4551***
	(0.1760)	(0.1251)	(0.1261)	(0.1264)	(0.1777)
Industry controls	Yes	Yes	Yes	Yes	Yes
N	2017	2017	2017	2017	2017
F-statistic	21.67***	21.87***	21.72***	17.79***	15.83***
R^2	0.1730	0.1733	0.1723	0.1726	0.1749

Note. Superscripts *, ** and *** represent statistical significance at the 10%, 5% and 1% level respectively.

5.2.2 HS2: Ticker characteristics and trading volume: mixed effects regression using firm size

In addition to the simple OLS regression focusing on the effect of ticker characteristics on change in market capitalization, once again regressions using interaction effects with firm size are performed. Firm size measure used is the market capitalization. Just as with the performed interaction effect regressions in subsection 5.1.2., the firms are placed in groups using the quintile of their firm size. This is represented by SQ1, SQ2, SQ3, SQ4 and SQ5 where SQ1 represents the biggest 20% of companies and SQ5 represents the smallest 20% of companies. Table 4 contains the regressions using the first three ticker characteristics, being ticker length, whether the ticker is an English word and ticker pronounceability. Due to the fact that the alphabetical bias in tickers is tested using multiple alphabetical groups, being the top 1%, 5%, 10%, 20% and 50%, these are placed in a separate table. In contrary to testing all alphabetical groups at the same time, as is done in subsection 5.1.1, I will now conduct a different test for every alphabetical group separately. This drastically decreases the complexity of the regression and makes the output less complicated to interpret.

Observations from the test outputs

Table 4 and Table 5 show the test outputs for the regressions using interaction effects and firm size. In the test using ticker length as the ticker characteristic of interest, no general effect was found. However, ticker length does seem to have a positive significant effect in the second Size Quintile which is even significant at 1%. In the test in which the dummy variable that indicates whether a ticker is an English word is focused on, a positive general effect was found. However, no interaction effect was found to be significant at any level. The last column of Table 4 presents the results of the regression focusing on the interaction effects of the Size Quintiles and ticker pronounceability. A positive general effect of ticker pronounceability on the trading volume was found. This is remarkable because in the tests without Size Quintiles in subsection 5.1.1 no significant effect for Ticker Pronounceability was found. In addition to this general effect, a negative significant interaction effect is found for Ticker Pronounceability and the lowest Size Quintile (SQ5). In the table containing the regression outputs for the interaction effects of the alphabetical groups and the Size Quintiles it can be seen that neither a general effect is found using 5% significance level, nor a interaction effect. Throughout all performed regressions, Size Quintile 2 (SQ2) remains highly significant at the 1% significance level. Furthermore, the control variables and constant remain highly significant at the 1% significance level. In contrast to the effects of the industry dummies in subsection 5.1.1, now all industry dummies have a significant effect of which only the effect of industry classification 'Industrials' is not significant at the 5% significance level.

Implications for the hypotheses

In hypothesis set 2, the main underlying hypothesis is that the effect of tickers that enjoy more investor attention on trading volume is especially pronounced among smaller firms. The first subhypothesis (2A) states that the negative effect of having little letters in one's ticker is more pronounced among smaller firms. This means that lowest quintiles a stronger and more negative effect is expected. However, at the 5% significance level, no effect was found at all for the smallest two Size Quintiles. In fact, the only significant effect found was a positive coefficient of 0.7352 for Size Quintile 2 (SQ2). This means that the effect of ticker length is not significantly different in the lower Size Quintiles than in Size Quintile (1). The effect of ticker length, if any, is therefore not found to be more pronounced among smaller firms. As a result, hypothesis 2A is rejected.

The second subhypothesis of hypothesis set 2 (2B) states that the positive effect of a ticker being an English word is more pronounced among smaller firms. This means that lowest quintiles a stronger and more positive effect is expected. In Table 4 it can be observed that a positive general effect was found. This effect is found to be significant at the 5% significance level. This means that the effect of a ticker being an English word is not significantly different in the lower Size Quintiles than in Size Quintile (1). As a result, hypothesis 2B is rejected.

The third subhypothesis (2C) states that the positive effect of having a pronounceable ticker is more pronounced among smaller firms. This means that lowest quintiles a stronger and more positive effect is expected. Remarkably, a positive general effect was found which is significant at the 5% significance level. This is remarkable because in subsection 5.1.1 it was concluded that ticker pronounceability does not have an effect on trading volume. In addition to the found general effect, there appears to be one significant interaction effect. The interaction effect of a ticker being pronounceable and the company being in the fifth Size Quintile (SQ5) is found to be negative and significant. Meaning the effect having a pronounceable ticker is weaker or even negative for companies in the lowest Size Quintile. This is the opposite of the hypothesized effect. As a result, hypothesis 2C is rejected.

The last subhypothesis of hypothesis set 2 (2D) states that the positive effect of a ticker appearing in the top when alphabetically ranked is more pronounced among smaller firms. This means that lowest quintiles a stronger and more positive effect is expected. In Table 5, the regressions using the alphabetical groups are presented. At the 5% significance level, no general effects of being in the top 1%, 5%, 10%, 20%, or 50% where found. Furthermore, no significant effects were found for any of the interaction terms as well. As no general effect was found and no interaction effects as well, it appears that alphabetical ranking does not affect trading volume in any way, regardless of the market capitalization of the firm. Therefore, hypothesis 2D is rejected.

Table 4: Regression output for the interaction effects on trading volume (1/2): Ticker length, whether the ticker is an English word and ticker pronounceability in combination with Size Quintiles.

	TC = Ticker Length	TC = Ticker Word	TC = Ticker Pronounceability
TC	0.0392	0.1496**	0.1454**
	(0.0404)	(0.0683)	(0.0592)
SQ2	0.7352***	0.1653***	0.1749***
	(0.2069)	(0.0515)	(0.0704)
SQ3	0.5250**	0.0917	0.1095*
	(0.2448)	(0.0602)	(0.0645)
SQ4	0.3358	0.1927***	0.1901**
	(0.2447)	(0.0710)	(0.0746)
SQ5	0.0924	-0.0499	0.0066
	(0.2964)	(0.0862)	(0.0919)
TC * SQ2	-0.1814***	-0.1190	-0.1219
	(0.0627)	(0.1073)	(0.0912)
TC * SQ3	-0.1327*	-0.0452	-0.0930
	(0.0719)	(0.1016)	(0.0912)
TC * SQ4	-0.0556	-0.1580	-0.1011
	(0.0700)	(0.1114)	(0.0896)
TC * SQ5	-0.0527	-0.0679	-0.2538**
	(0.0817)	(0.1438)	(0.1083)
Percentage Afloat	0.0110***	0.0111***	0.0110***
	(0.0009)	(0.0009)	(0.0009)
LogSales	-0.0505***	-0.0469***	-0.0470***
	(0.0169)	(0.0168)	(0.0169)
LogDebt/Equity ratio	0.0110	0.0124	0.0131
	(0.0138)	(0.0136)	(0.0137)
LogMarket/Book ratio	0.0172	0.0133	0.0153
	(0.0222)	(0.0222)	(0.0222)
Constant	0.8054***	0.8690***	0.8595***
	(0.3669)	(0.1610)	(0.1630)
Industry controls	Yes	Yes	Yes
N	2017	2017	2017
F-statistic	18.08	17.11	17.09
R^2	0.1902	0.1875	0.1880

Note. Superscripts *, ** and *** represent statistical significance at the 10%, 5% and 1% level respectively.

Table 5: Regression output for the interaction effects on trading volume (2/2): Alphabetical groups in combination with Size Quintiles.

	Top 1%	Top 5%	Top10%	Top 20%	Top 50%
Top X%	-0.2060	-0.0358	-0.0808	-0.0243	-0.0366
	(0.1550)	(0.1077)	(0.0902)	(0.0703)	(0.0555)
SQ2	0.1290***	0.1312***	0.1306***	0.1454***	0.1535***
	(0.0486)	(0.0495)	(0.0502)	(0.0521)	(0.0658)
SQ3	0.0764	0.0731	0.0609	0.0633	0.0676
	(0.0573)	(0.0576)	(0.0586)	(0.0584)	(0.0690)
SQ4	0.1575**	0.1609**	0.1581**	0.1464**	0.0739
	(0.0691)	(0.0692)	(0.0696)	(0.0698)	(0.0799)
SQ5	-0.0752	-0.0809	-0.0869	-0.0843	-0.1122
	(0.0848)	(0.0841)	(0.0846)	(0.0867)	(0.0997)
Top X% * SQ2	0.6308	0.0096	0.0337	-0.0510	-0.0402
	(0.6630)	(0.1875)	(0.1435)	(0.1058)	(0.0827)
Top X% * SQ3	0.0411	-0.0224	0.1539	0.0736	0.0198
	(0.3964)	(0.1805)	(0.1383)	(0.1165)	(0.0839)
Top X% * SQ4	-0.1320	-0.1886	-0.0048	0.0474	0.1620*
	(0.2966)	(0.1641)	(0.1335)	(0.1094)	(0.0852)
Top X% * SQ5	-0.0684	-0.0484	0.1293	0.0532	0.0843
	(0.1812)	(0.3172)	(0.1575)	(0.1163)	(0.0997)
Percentage Afloat	0.0110***	0.0110***	0.0110***	0.0110***	0.0110***
	(0.0009)	(0.0009)	(0.0009)	(0.0009)	(0.0009)
LogSales	-0.0474***	-0.0491***	-0.0478***	-0.0476***	-0.0466***
	(0.0171)	(0.0170)	(0.0170)	(0.0169)	(0.0168)
LogDebt/Equity	0.0126	0.0129	0.0121	0.0121	0.0121
ratio	(0.0136)	(0.0136)	(0.0136)	(0.0136)	(0.0136)
LogMarket/Book	0.0162	0.0140	0.0155	0.0154	0.0154
ratio	(0.0224)	(0.0223)	(0.0223)	(0.0222)	(0.0222)
Constant	0.9149***	0.9360***	0.9249***	0.9171***	0.9232***
	(0.1623)	(0.1620)	(0.1612)	(0.1603)	(0.1629)
Industry controls	Yes	Yes	Yes	Yes	Yes
N	2017	2017	2017	2017	2017
F-statistic	Unobserved?	16.98	16.88	16.82	16.93
R^2	0.1864	0.1862	0.1858	0.1856	0.1874

Note. Superscripts *, ** and *** represent statistical significance at the 10%, 5% and 1% level respectively.

5.2 Ticker characteristics and change in market capitalization

5.2.1 HS3: Ticker characteristics and change in market capitalization: simple OLS regressions

In Table 7 the results from regression equation (3) are quantified. This includes the four separate regressions for each ticker characteristic and one regression including all ticker characteristics. The results illustrate the relationships between the ticker characteristics and change in market capitalization. Furthermore, the control variables are included in all regressions. This means that also the dummy variables for the industry classifications are included in the model.

Observations from the test outputs

While performing the tests, once again Stata by itself omitted the industry classification 'Utilities' due to collinearity. This could mean that there is another highly correlated independent variable included in the model. Unfortunately, Stata does not show what the variable is that is highly correlated to the industry classification 'Utilities'. Another reason why the binary variable for 'Communication Services has been left out is because there has to be a base effect for the industries. The other industry effects are then relative to this base effect. Most of the dummy variables for the industry classifications are found to be highly significant in every performed test. All coefficients are significant and negative, except for the effect of 'Materials', this effect is not significant at any level. All control variables are found to be highly significant, even at the 1% significance level in every regression in Table 7. The F-statistic is relatively high and highly significant for all models, while being lower in the regressions incorporating alphabetical ranking as a result of the inclusion of more variables with limited explanatory power. The adjusted R^2 of all models is between the 0.41 and 0.43, meaning that about 41% to 43% of the variation in the dependent variable is explained by the model. Other variation in the dependent variable might be explained by company specific developments.

Ticker length has negative effect on the change in market capitalization, which is not in line with the hypothesis based on academic research. This effect is significant even at the 5% significance level if the effect was tested separately and even at the 1% significance level in the regression using all ticker characteristics. Whether the ticker is an English word does seem to have a negative effect on the change in market capitalization, which is in line with the hypothesis based on the literature. The effect is statistically significant at the 1% significance level both when tested separately and in the regression using all ticker characteristics. In general, the ticker pronounceability seems to have no effect on the change in market capitalization. No significant effect was found in both the test using solely ticker pronounceability and the test using all ticker characteristics. For the dummies for the alphabetical groups, only an effect was found for the alphabetical group the 10% group which is positive. Meaning that firms in the alphabetical top 10% have deflated less than firms outside the top 10%. This is the contrary of the hypothesized effect. In the regression focusing solely on the alphabetical bias, the effect is only significant at the 10% significance level while in the regression using all ticker characteristics, it is significant at the 5% level. The logarithm of the sales seems to have a positive a highly significant effect. The same is true for the debt-to-equity ratio, both being significant at the 1% significance level. The market-to-book ratio has a significant negative effect. Also being highly significant, even at the 1% significance level. It makes sense, that companies with a high market-to-book value are found to decrease more in price during a downfall in market sentiment. These companies are often high growth companies generating high risk, high reward profits. As the speculative retail investors have a taste for stocks with lottery-like payoffs (Mitton & Vorkink, 2007; Kumar, 2009b) they might drive up especially the prices of these companies during times of higher investor sentiment. As a result, the prices of these companies might fall the most when market sentiment comes down.

Implications for the hypotheses

In this set of hypotheses, the main underlying hypothesis is that more recognizable ticker and tickers that are easier to remember or find have should have been deflated more heavily during the fall in investor sentiment. The first subhypothesis (3A) states that companies with tickers that contain less letters generally deflated more heavily. This means that a significant positive effect should have been found for the variable Ticker Length. In the first performed regression focusing on this Ticker Length a negative coefficient of -2.0517 was found. This means that for each additional letter in a ticker, the change in market capitalization from December 2021 to June 2022 will go down by 2.0517 percentage point. This effect is found to be significant at the 5% significance level. In the regression that includes all ticker characteristics looked at, a negative significant coefficient was found as well, being -2.8536. In this regression, the effect is even significant at the 1% significance level. Following the results from this set of performed regressions, it seems that in general the number of letters in a ticker had a negative effect on the change in market capitalization in the specified timeframe, while a positive relationship was expected. As a result, hypothesis 3A is rejected.

The second subhypothesis (3B) states that companies with tickers that resemble an English word have been deflated more as well. This means that a significant negative effect should have been found for the variable Ticker Word. In the first performed regression focusing on this Ticker Word an effect of -4.1521 was found. This means that if the ticker is an English word, in general the change in market capitalization will be 4.1521 percentage point lower than for similar companies with a ticker that is not an English word. This effect is found to be significant at the 1% significance level. In the regression that includes all ticker characteristics looked at, a negative coefficient was found as well, being -4.7071. This effect is found to be significant at the 1% significance level as well. Following the results from the set of performed regressions, it seems that whether a ticker is an English word has a significant negative effect on the change in market capitalization from December 2021 to June 2022. Therefore, hypothesis 3B is not rejected.

The third subhypothesis of hypothesis set 3 (3C) states that companies with pronounceable tickers generally have deflated more in the specified timeframe. This means that a significant negative effect should have been found for the variable Ticker Pronounceability. In the first performed regression focusing on this Ticker Pronounceability a negative effect of -1.3512 was found. This means that if a ticker is pronounceable, the change in market capitalization will be 1.3513 percentage point lower than that of a similar company without a pronounceable ticker. However, this effect is found to be insignificant even at the 10% significance level. In the regression that includes all ticker characteristics looked at, no significant effect was found as well. Following the results from the first set of performed regressions, it seems that in general the pronounceability of a ticker does not affect the change in market capitalization during the decline in market sentiment. As a result, hypothesis 3C is rejected.

The last hypothesis that is not focused on interaction effects in hypothesis set 3 (3D) states that tickers that are higher in the alphabetical order have deflated more than companies with stock tickers that are lower in the alphabetical order. This means that a significant negative effect should have been found for the variables Alphabetical *X*%. In both the regression focusing solely on the alphabetical bias and the regression that uses all ticker characteristics, a significant positive effect was found for the binary variable that indicated whether a company was in the top 10%. This is the only significant effect that is found in this set of performed regressions. This result indicates that there is only a significant effect of companies being in the alphabetically top 10%. This effect is significant at the 10% significance level and in the regression with all the ticker characteristics, it is found to be significant at the 5% significance level. However, based on the literature, it was expected that being in the alphabetically top would have a negative impact on the change in market capitalization. Following the results from the first set of performed regressions, hypothesis 3D is therefore rejected.

Table 6: Regression outputs for ticker characteristics and change in market capitalization.

	(1)	(2)	(3)	(4)	(5)
Ticker Length	-2.0517**				-2.8356***
	(0.9729)				(0.9939)
Ticker Word		-4.1521***			-4.7071***
		(1.5933)			(1.7803)
Pronounceability			-1.3513		-0.3547
			(1.3124)		(1.4470)
Alphabetical 1%				7.1109	7.0709
				(6.8355)	(6.8171)
Alphabetical 5%				-4.7800	-5.2432
				(4.0792)	(4.0726)
Alphabetical 10%				8.2811*	8.5769**
				(3.3218)	(3.3369)
Alphabetical 20%				-2.9054	-2.8351
				(2.2134)	(2.2077)
Alphabetical 50%				0.5349	0.5860
				(1.3987)	(1.3960)
LogSales	3.2860***	3.4862***	3.4741***	3.4473***	3.2042***
	(0.3731)	(0.3622)	(0.3626)	(0.3634)	(0.3732)
LogDebt/Equity	3.0037***	3.0543***	3.0656***	3.1041***	2.9735***
ratio	(0.4797)	(0.4782)	(0.4790)	(0.4789)	(0.4791)
LogMarket/Book	-8.4665***	-8.3777***	-8.5042***	-8.4606***	-8.2468***
ratio	(0.7272)	(0.7283)	(0.7275)	(0.7282)	(0.7287)
Constant	-16.5048***	-23.6510***	-23.9712***	-24.8569***	-12.5193**
	(5.0244)	(4.4419)	(4.0377)	(4.4689)	(5.9876)
Industry controls	Yes	Yes	Yes	Yes	Yes
N	2019	2019	2019	2019	2019
F-statistic	67.61***	68.42***	67.56***	53.57***	47.15***
R^2	0.4194	0.4201	0.4184	0.4205	0.4246

Note. Superscripts *, ** and *** represent statistical significance at the 10%, 5% and 1% level respectively.

5.2.2 HS4: Ticker characteristics and trading volume: mixed effects regression using firm size

In addition to the simple OLS regression focusing on the effect of ticker characteristics on change in market capitalization, once again regressions using interaction effects with firm size are performed. Firm size measure used is the market capitalization. Just as with the performed interaction effect regressions in subsection 5.1.2., the firms are placed in groups using the quintile of their firm size. This is represented by SQ1, SQ2, SQ3, SQ4 and SQ5 where SQ1 represents the biggest 20% of companies and SQ5 represents the smallest 20% of companies. Table 6 contains the regressions using the first three ticker characteristics, being ticker length, whether the ticker is an English word and ticker pronounceability. Due to the fact that the alphabetical bias in tickers is tested using multiple alphabetical groups, being the top 1%, 5%, 10%, 20% and 50%, these are placed in a separate table. In contrary to testing all alphabetical groups at the same time, as is done in subsection 5.2.1, I will now conduct a different test for every alphabetical group separately. This drastically decreases the complexity of the regression and makes the output less complicated to interpret.

Observations from the test outputs

Table 8 and Table 9 show the test outputs for the regressions using interaction effects and firm size. In the test using ticker length as the ticker characteristic of interest, it is observable that the general effect of ticker length is negative and significant at the 10% significance level but not at the 5% significance level. Neither the Size Quintiles nor the interaction effects of ticker length and the Size Quintiles are found to be significant. In the test in which the dummy variable that indicates whether a ticker is an English word is focused on, the general effect is insignificant. In this particular test, the Size Quintiles all are highly significant at the 1% significance level. Remarkably, the interaction effect of the lowest Size Quintile and the variable Ticker Word is negative and significant at the 5% significance level. The last column of Table 8 presents the results of the regression focusing on the interaction effects of the Size Quintiles and ticker pronounceability. There is no general effect of ticker pronounceability on the change in market capitalization, nor was there found any significant interaction effects. The Size Quintiles in were found to be significant at the 1% significance level. In the table containing the regression outputs for the interaction effects of the alphabetical groups and the Size Quintiles it can be seen that no general effect is found using 5% significance level. However, one significant interaction effect was found. The interaction coefficient for being in the lowest Size Quintile and being in the top 1% when alphabetically ordered is found to be negative and significant at the 1% significance level. In the test using the alphabetical groups, the Size Quintiles are always significant at the 1% significance level. Throughout all performed regressions the control variables and constant remain highly significant at the 1% significance level.

Implications for the hypotheses

In hypothesis set 4, the main underlying hypothesis is that the deflating effect of tickers that enjoy more investor attention is especially pronounced among smaller firms. The first subhypothesis (4A) states that the deflating effect of having little letters in one's ticker is more pronounced among smaller firms. This means that lowest quintiles a stronger and more positive effect is expected. However, at the 5% significance level, no effect was found at all. Neither of the interaction effects have any significance. Meaning that in neither of SQ2, SQ3, SQ4 or SQ5 there is a different effect of ticker length on change in market capitalization in comparison with SQ1. The absence of such effects indicates that the deflating effect of shorter tickers, if any, is not especially pronounced among smaller firms. As a result, hypothesis 4A is rejected.

The second subhypothesis of hypothesis set 4 (4B) states that the deflating effect of a ticker being a word is more pronounced among smaller firms. This means that lowest quintiles a stronger and more negative effect is expected. In Table 8 it can be observed that no general effect was found. However, when looking at the interaction effects, it becomes clear that there is indeed a negative effect of a ticker being a word in the lowest quintile (SQ5). This effect is found to be significant at the 5% significance level. This indicates that the changes in market capitalization for firms in the lowest quintile and a ticker that resembles an English word are significantly lower. As there is no effect of the ticker being an English word found among other quintiles, the effect is found to be solely present among smaller firms. As a result, hypothesis 4B is not rejected.

The third subhypothesis (4C) states that the deflating effect of having a pronounceable ticker is more pronounced among smaller firms. This means that lowest quintiles a stronger and more negative effect is expected. However, at any significance level, no effect was found at all. Neither of the interaction effects have any significance. Meaning that in neither of SQ2, SQ3, SQ4 or SQ5 there is a different effect of ticker pronounceability on change in market capitalization in comparison with SQ1. The absence of such effects indicates that the deflating effect of pronounceable tickers, if any, is not especially pronounced among smaller firms. As a result, hypothesis 4C is rejected.

The last subhypothesis of hypothesis set 4 (4D) states that the deflating effect of a ticker appearing in the top when alphabetically ranked is more pronounced among smaller firms. This means that lowest quintiles a stronger and more negative effect is expected. In Table 9, the regressions using the alphabetical groups are presented. At the 5% significance level, no general effects of being in the top 1%, 5%, 10%, 20%, or 50% where found. However, when looking at the interaction effects, there is one interaction effect that appears to be significant even at the 1% significance level. This effect is found to be significant at the 5% significance level. This indicates that the changes in market capitalization for firms in the lowest quintile and a ticker that appears in the top 1% when alphabetically listed, are significantly lower. This effect is only found in the regression using the split between the alphabetical top 1%, not in the regressions using the other alphabetical groups. As there is no effect of the ticker being on top of alphabetical listings among other quintiles, the effect is found to be solely present among smaller firms. As a result, hypothesis 4D is not rejected.

Table 7: Regression output for the interaction effects on change in market capitalization (1/2): Ticker length, whether the ticker is an English word and ticker pronounceability in combination with Size Quintiles.

	TC = Ticker Length	TC = Ticker Word	TC = Ticker Pronounceability
TC	-2.3692*	-3.0862	-2.3533
	(1.3792)	(2.3917)	(2.1476)
SQ2	10.9550	6.2908***	6.4870***
	(6.9715)	(1.8464)	(2.0388)
SQ3	3.3935	8.7964***	8.0138***
	(7.9443)	(2.2111)	(2.3017)
SQ4	12.2174	8.4984***	8.5678***
	(9.2372)	(2.6722)	(2.8269)
SQ5	21.9500	19.0036***	17.8991***
	(13.7000)	(3.6950)	(3.7473)
TC * SQ2	-1.0135	4.7237	2.4685
	(2.0535)	(4.4016)	(3.2091)
TC * SQ3	1.6595	-1.7736	1.7071
	(2.2643)	(3.7895)	(3.5076)
TC * SQ4	-0.5412	4.5613	2.7571
	(2.5351)	(4.7644)	(3.5981)
TC * SQ5	-0.9382	-11.4066**	-0.9506
	(3.4620)	(5.6133)	(4.8802)
LogSales	5.6701***	5.7475***	5.7546***
	(0.5922)	(0.5903)	(0.5972)
LogDebt/Equity ratio	2.1728***	2.2983***	2.3008***
	(0.5175)	(0.5098)	(0.5120)
LogMarket/Book ratio	-5.9392***	-6.1112***	-6.1460***
	(0.8850)	(0.8906)	(0.8893)
Constant	-45.6210***	-52.8109***	-53.03400***
	(7.4044)	(5.6829)	(5.8037)
Industry controls	Yes	Yes	Yes
N	2019	2019	2019
F-statistic	46.65	45.47	44.83
R^2	0.4299	0.4326	0.4282

Note. Superscripts *, ** and *** represent statistical significance at the 10%, 5% and 1% level respectively.

Table 8: Regression output for the interaction effects on changes in market capitalization (2/2): Alphabetical groups in combination with Size Quintiles.

	Top 1%	Top 5%	Top10%	Top 20%	Top 50%
Top *X* %	14.0799*	4.6106	4.9075	2.4853	-0.1921
	(7.3737)	(4.0592)	(3.2047)	(2.4820)	(1.9630)
SQ2	7.2083***	7.0137***	7.1932***	7.0192***	6.7417***
	(1.7731)	(1.8084)	(1.8189)	(1.9322)	(2.4703)
SQ3	8.3332***	8.5208***	8.8425***	8.7246***	7.5405***
	(2.1077)	(2.1256)	(2.1768)	(2.2260)	(2.5579)
SQ4	9.3485***	9.5633***	9.4508***	10.3158***	9.4888***
	(2.6042)	(2.6081)	(2.6532)	(2.6732)	(3.0182)
SQ5	17.4747***	17.9285***	17.9240***	18.5451***	16.9203***
	(3.6241)	(3.6316)	(3.4661)	(3.4960)	(4.0232)
Top *X* % * SQ2	-0.9472	3.9172	1.5804	0.9759	1.1810
	(9.5401)	(6.5277)	(5.4431)	(3.6725)	(3.0172)
Top *X* % * SQ3	-1.9611	-0.7789	-2.1086	-0.7194	2.2419
	(10.1768)	(6.5131)	(5.4398)	(3.9410)	(3.0415)
Top *X* % * SQ4	-19.7920	-4.9032	-0.4594	-4.4562	0.0738
	(15.4564)	(6.6672)	(5.5398)	(4.3237)	(3.3344)
Top *X* % * SQ5	-37.7269***	-10.9080	-1.4531	-4.7365	1.7782
	(8.0140)	(9.9483)	(9.8334)	(5.8724)	(4.2757)
LogSales	5.6401***	5.6969***	5.7667***	5.7351***	5.7730***
	(0.5988)	(0.5986)	(0.6171)	(0.5973)	(0.5976)
LogDebt/Equity	2.3459***	2.3309***	2.3165***	2.3221***	2.3083***
ratio	(0.5123)	(0.5144)	(0.5135)	(0.5123)	(0.5112)
LogMarket/Book	-6.2381***	-6.1422***	-6.1181***	-6.1585***	-6.1211***
ratio	(0.8902)	(0.8881)	(0.8980)	(0.8842)	(0.8913)
Constant	-53.0034***	-53.5360***	-54.4806***	-54.0778***	-53.9539***
	(5.7467)	(5.7402)	(5.8965)	(5.7514)	(5.8384)
Industry controls	Yes	Yes	Yes	Yes	Yes
N	2019	2019	2019	2019	2019
F-statistic	Unobserved?	43.76	44.43	44.65	44.09
R^2	0.4289	0.4287	0.4292	0.4284	0.4280

Note. Superscripts *, ** and *** represent statistical significance at the 10%, 5% and 1% level respectively.

5.3 Robustness checks

5.3.1 Replacing the market capitalization for Size Quintiles in subsection 5.1.1

In subsection 5.1.2 it became clear that the results were somewhat contradictory. On the one hand, it was concluded in subsection 5.1.1 that whether a ticker is an English word or is pronounceable does not affect the trading volume of the firm. On the other hand, in subsection 5.1.2 the ticker characteristics are tested again using interaction effects and it actually shows that there are significant effects for pronounceable tickers and tickers that resemble an English word. Besides the interaction effects nothing changed, except for one thing: the logarithm of the market capitalization was left out as the automatically included size quintiles were indirectly controlling for the market capitalization as well. As the market capitalization is not significant in any of the tests, I replace them with the same Size Quintiles that are used in the tests with the interaction terms. The results can be found in Table A in Appendix A. From these results, it can be seen that all effects remain insignificant at the 5% significance level except for the effect of a ticker being an English word. This effects now appears to be significant in the regression using only that ticker characteristic. In the regression that uses all ticker characteristics, it is observable that this effect is no longer significant at the 5% significance level. This in combination with the lowered F-statistic of the models makes that I maintain the conclusion which is draw in section 5.1.1. All hypotheses in hypothesis set 1, which state that potential attention-grabbing ticker characteristics affect trading volume, are rejected.

5.3.2 Excluding microcaps from the sample

In many studies in empirical corporate finance it is proven that excluding microcap stocks could have significant impact on the found effects in a study. Hou et al. (2020), who study anomalies in the US stock market, argue that if microcaps are sufficiently controlled for, many broadly accepted anomalies disappear. Qiao (2019) and Hollstein (2020) find similar evidence in the Chinese market and other international markets respectively. On the other hand, excluding microcaps can also result in better performing models (Fama & French, 2012). Therefore, I perform the tests in subsections 5.1.1 and 5.1.2 again without the companies with a market capitalization below the $300 million. The sample then includes 1917 companies in the tests on trading volume and 1919 companies in the tests on changes in market capitalizations, which is 100 less than in the original sample. This might seem like just a small reduction in comparison with the original sample, but in the original sample many firms were left out already for which not all information was available. As smaller stocks are more likely to have missing information, namely the smaller companies were filtered out already in the original sample.

The results of the tests in which microcaps are excluded are presented in Table A2 and Table A3 in Appendix A. From these tables it becomes clear that the results do not differ from the original tests carried out in subsections 5.1.1 and 5.2.1. In the tests focusing on the effect of ticker characteristics on trading volume, no effects are found that are significant at the 5% significance level. In these tests, both the percentage afloat and the logarithm of the sales are found be significant at the 5% significance level. The R-squared statistics are slightly higher for the tests excluding microcaps in comparison with the original test. The tests focusing on the effect of ticker characteristics on changes in market capitalizations are consistent with the tests using the original sample. For ticker length and whether a ticker is word, a negative effect was found that remains significant at the 5% significance level even when all ticker characteristics are included. This effect of ticker length is not the hypothesized effect. Ticker pronounceability has no effect on the changes in market capitalizations and neither an alphabetical bias was found. Which was also not found in the original tests. However, there was an alphabetical bias found in the tests using interaction effects with Size Quintiles. In the original tests, a significant negative effect was found for being in the top 1% when alphabetically listed among the lowest quintile. The same tests are performed with microcaps excluded and the results are presented in Table A4. From this table, it can be observed that the same negative effect is also present when microcaps are excluded from the sample. Altogether, it can be concluded that excluding microcaps from the sample does not affect the found effects in this study.

5.3.3 Testing external validity using the Toronto Stock Exchange

In section 5.2, it was found that multiple ticker characteristics seem to have an effect on the change in market capitalization of a firm between December 2021 and June 2022. Based on section 5.2 ticker length has a negative effect on the change in market capitalization of a firm while a positive effect was expected based on the literature. Whether the ticker was an English word was found to have a negative effect, consistent with the hypothesized effect. Furthermore, there seems to be some evidence for alphabetical bias among the smallest firms. In order to test the external validity of these results, I run the same test but then for companies listed on the Toronto Stock Exchange (TSX).

The data collection is done in exactly the same way as for the original sample. This means that the change in market capitalization from the first of December 2021 to the first of June 2022 is calculated. The logarithm of the sales, market-to-book ratios and debt-to-equity ratios are calculated and the market-to-book ratios and debt-to-equity ratios are winsorized at the 1% level. Once again Real Estate Investment Trusts (REITs) and Special Purpose Acquisition Companies (SPACs) are excluded from the data. I only keep the observations of which I was able to calculate all the variables. This are eventually 521 observations. For these observations, the independent variables were determined in exactly the same way as was done in the original sample.

In Table A5 in Appendix A, the results can be observed of the same regression as in subsection 5.2.1, which uses regression equation (3). From the table it becomes clear that the significant negative effect for ticker length is not only present among companies listed on the New York Stock Exchange but also among companies listed on the Toronto Stock Exchange. The negative coefficient among companies listed on the Toronto Stock exchange is highly significant, even at the 1% significance level. The negative effect of a ticker being an English word that was found in the original sample is not found for the companies listed on the Toronto Stock Exchange. Both in the test using Ticker Word as only ticker characteristic and the test using all ticker characteristics, no significant effect was found. The same holds for ticker pronounceability. In the regression using only the alphabetical groups and not the other ticker characteristics, it looks like being in the top 1% has a negative effect on the change in market capitalization. However, this effect is no longer significant at the 5% significance level when the other ticker characteristics are included.

Hypotheses 3B and 3C state that the change in market capitalization is lower for companies with tickers that resemble an English word and companies with pronounceable tickers. From the tests performed using the data from the Toronto Stock Exchange, it seems like the hypotheses 3B and 3C should be rejected after all. However, one important sidenote is to be made. The framework used in order to test builds on the assumption that prices of certain equities get overinflated during times of higher investor sentiment due to speculative traders who typically do not have a professional background. Barber & Odean (2008) hypothesized that many investors only consider stocks that have first caught their attention as attention is a scarce resource. One potential explanation for not finding the negative effect of a ticker being an English word could be that there was limited speculation to begin with. As traders with limited attention are potentially trading on the best-known exchange(s). As the NYSE is the biggest stock exchange in the world (New York Stock Exchange, Inc., n.d.), it might be the case that speculative traders mostly trade on the New York Stock Exchange and other bigger exchanges (such as the Nasdaq) instead of the Toronto Stock Exchange. This would then lead to limited asset inflation during times of high investor sentiment and limited deflation when investor sentiment falls, which could explain why irrational biases are limited on relatively lesser-known exchanges such as the Toronto Stock Exchange. As a result, I will not reject hypotheses 3B and 3C after all. However, it is important to stress that the results found in this paper are not guaranteed to be applicable to other stock exchanges as well. The appearance of behavioral biases might depend heavily on exchange characteristics.

5.4 Hypothesis overview

The table below shows a clear overview of the hypothesized effects and whether these effects were found in the data.

Table 9: Summary of the found effects of the different ticker characteristics examined

Ticker Characteristic	A: Ticker Length	B: Ticker Word	C: Ticker Pronounceability	D: Alphabetical Bias
Hypothesis set 1: Affects trading volume in full sample	Rejected	Rejected	Rejected	Rejected
Hypothesis set 2: Effect more pronounced among smaller firms	Rejected	Rejected	Rejected	Rejected
Hypothesis set 3: Affects change in market capitalization	Rejected	Not rejected	Rejected	Rejected
Hypothesis set 4: Effect more pronounced among smaller firms	Rejected	Not rejected	Rejected	Not rejected

Note. It might seem contradicting that no potential alphabetical bias was found in hypothesis set 3 but this effect was more pronounced among smaller firms. However, this means that if no split was made between bigger and smaller companies, no significant effect was found. At the same time, the hypothesized effect was found for smaller companies when including interaction effects with firm size and therefore the hypothesized effect can be regarded as more pronounced among smaller firms.

6 Conclusion and limitations

6.1 Conclusion

In this paper, the potential effects of multiple stock ticker characteristics on the company's trading volume and valuations have been examined. In this way, this paper tries to answer the following research quenstion: ***'How do stock ticker characteristics affect trading activity and company valuations?'*** Moreover, it was examined whether the potential effects of these ticker characteristics were more pronounced among smaller firms. In order to test the effect on market valuations of companies, this research made use of a special case study based on the research by Durham and Santhanakrishnan (2016). In this case study, it is motivated that in periods of high investor sentiment more non-professional investors, who more heavily suffer from attention bias, inflated prices of assets that caught their attention more. It is then hypothesized that tickers characteristics that might attract more investors cause their assets to be more inflated during high investor sentiment. As a result, these specific assets should have deflated more when investor sentiment subsequently declined. The ticker characteristics focused on were ticker length, whether the ticker is an English word, whether the ticker is pronounceable and potential alphabetical bias.

The answer on the research question is that ticker characteristics do not affect trading volume while ticker characters appear to play a role in company valuations. From the tests focusing on the change in market capitalization between December 2021 and June 2022, it turns out that ticker length negatively affects these changes instead of positive. Meaning that in times of declining investor sentiment, companies with longer tickers seem to be more heavily deflated. This is the opposite effect of what was hypothesized. This effect is not found to be different in different firm size quintiles. Furthermore, this effect is also found in the regressions performed using data from the Toronto Stock Exchange. From the performed regressions it turns out that a ticker being a word negatively affects these changes in the full data set. This effect remains highly significant also when the other ticker characteristics are included. Effectively meaning that in times of declining investor sentiment, companies with tickers that resemble an English word seem to be more heavily deflated. When including interaction effect for firm size, the effect was found to be only significant among the smallest 20% of companies. From the tests focusing on the change in market capitalization, it turns out that a ticker being pronounceable does not affects these changes in the market capitalization. In the test using interaction effects with the Size Quintiles, no significant effect was found. The fourth and last ticker characteristic examined was alphabetical ranking. From the tests using groups for the top 1%, 5%, 10%, 20% and 50%, it seems like there is no evidence indicating that alphabetical ranking could be affecting changes in market capitalization to any extent. From the tests focusing on the change in market capitalization, it turns out that a ticker being in the top 1% actually could lead to more negative changes in the market capitalization during a downfall of investor sentiment, in line with the hypothesis. This effect is significant at the 1% significant level.

In hypothesis 3A it is stated that firms with tickers with less letters should have deflated more during the downfall in investor sentiment. This is based on the assumption that shorter tickers are easier to recognize and remember, causing overinflation in speculative times of higher investor sentiment. In other words, companies with longer tickers should have deflated less. Therefore, a positive effect of ticker length on the change in market capitalizations was expected. However, in the tests conducted in subsection 5.2.1 a negative coefficient was found which was significant at the 5% significance level. Moreover, while doing the same tests using the data of the Toronto Stock Exchange, a negative coefficient was found which was even significant at the 1% significance level. As these found effects are the opposite of the hypothesized effect, it remains the question what causes these negative effects. Within the framework based on investor attention used in this paper, it seems unlikely that longer tickers attract more investors.

As no research has been done before on ticker length and trading volume or asset prices, there is no work to compare the results to. To my best knowledge, this research has contributed to existing literature by finding a significant relationship between ticker length and company valuations. Research by Jin et al. (2019) did find a premium for companies with three-character names, but tickers and companies have such different properties and limitations that it would not be a good comparison. The ticker fluency developed by Travers & Olivier (1978), which is used in many academic papers is a mix of pronounceability and being an English word. To my best knowledge, there is also no current research that examines the pure effect of a ticker being an English word. However, generally it is found in academic literature that more fluent company names and tickers lead to higher returns and valuation premia (Chan et al., 2018; Hsu et al., 2022; Montone et al., 2023). An important sidenote is that Montone et al. (2023) look at returns based on stock prices while I have focused on changes in market capitalization. Furthermore, the research done by Montone et al. makes use of the timeframe 1981 to 2008. This period might be hard to compare with more recent times in which trading has become a lot more accessible to the general public. This paper finds that tickers that are a word lead to heavier deflation when investor sentiment declines, implying more heavier inflation in times of high investor sentiment. These results are therefore in line with current literature. Alter & Oppenheimer (2006) find that more pronounceable tickers lead to higher returns from IPOs, while Peterburgsky (2017) did not find significant effect of ticker pronounceability in both risky and less risky assets. My results are in line with the results of Peterburgsky as I do not find any significant effects of ticker pronounceability as well. Lastly, Jacobs & Hillert (2016) and Itzkowitz & Itzkowitz (2017) find alphabetical bias in trading activity. My results contradict these papers as I do not find a significant alphabetical bias in trading volume. Itzkowitz & Itzkowitz (2017) also find alphabetical bias in firm values, where firms that appear on top of alphabetical listings enjoy a premium. My findings are in line as I find that the smallest firms that are in the top 1% of alphabetical listings, the deflation during the fall of investor sentiment was more extreme. Implying that these assets have been overinflated during times of higher investor sentiment.

Altogether, this paper has shed new light on the effects of ticker characteristics. They do not seem to affect trading volume, but they could affect asset inflation in times of high investor sentiment.

6.2 Limitations and recommendation

Although this research finds some significant effects, it should be noted that the research has its limitations as well. The most important limitation of this research is that there are many factors affecting trading volume or asset valuations, which cannot all be included in the regression models. It is tried to include the most important control variables to minimize potential omitted variable bias. However, the R-Squared statistics are at 0.4326 at most. For the test on trading volume, they are even lower. This means that a lot of the variation in the dependent variable is still to be explained. This might indicate that there are other variables that are not observed play an important role. One example of such a variable is firm specific news as this could significantly influence both trading volume and changes in market capitalizations. However, firm specific news is a variable that is both hard to define and hard to quantify, making it difficult to actually incorporate into the models.

In addition to this omitted variable bias, there might also be limitations with the measurement of the independent variables. Ticker length, a ticker being an English word and alphabetical bias are really straightforward. However, for the measurement of ticker pronounceability uses a strict criterion that might be discussable. The criteria basically use the logic that tickers are pronounced as words, using the pronounceability of syllables. However, a ticker can also be pronounced as an abbreviation. For example, the ticker "DB" would not be classified as a pronounceable ticker using the strict criterion used in this paper. But one can pronounce the letters as an abbreviation separately instead of as a syllable. In that case the ticker would be pronounced as "DEEBY" or "DEEBEE". The limitation of the variable ticker pronounceability is thus that the tickers "DB" and "DEEBY" are possibly generally pronounced the same but "DB" is categorized as not pronounceable and "DEEBY" is pronounced as pronounceable. Another limitation in the tests where potential differences in effects among different firm sizes are examined is the split in the data for firm sizes. The data has been split after each quintile but possibly, the effect of certain tickers characteristics might be different in for example the top 5% of firms based on firm size. Generally speaking, it might be argued that using quintiles is already a quite good classification and the effects already seem to differ between different data splits based on quintiles. The fact that there are already differences found in effects might be regarded as a positive signal for a reasonable split. On the other hand, it remains fairly unknown where the differences of the effects truly come into play.

Other potential causes for endogeneity could be reverse causality and simultaneity. However, in this particular subject, the role of these biases seems to be very limited. This is due to the fact that a ticker of a company is rarely changed and is rarely changed. Moreover, the idea that a company is changing its ticker due to its trading volume or (changes in) stock prices seems rather farfetched. However, I would argue for an exception for ticker length. In hypothesis 3A it is stated that firms with tickers with less letters should have deflated more during the downfall in investor sentiment. This is based on the assumption that shorter tickers are easier to recognize and remember, causing overinflation in speculative times of higher investor sentiment. In other words, companies with longer tickers should have deflated less. Therefore, a positive effect of ticker length on the change in market capitalizations was expected. However, in the tests conducted in subsection 5.2.1 a negative coefficient was found which was significant at the 5% significance level. Moreover, while doing the same tests using the data of the Toronto Stock Exchange, a negative coefficient was found which was even significant at the 1% significance level. As these found effects are the opposite of the hypothesized effect, it remains the question what causes these negative effects. Within the framework based on investor attention used in this paper, it seems unlikely that longer tickers attract more investors. It seems more likely that ticker length is somehow correlated with another variable which is negatively correlated with the changes in market capitalization. Examples of such variables could be the debt-to-equity ratio. Firms that have been around for longer have chosen the short tickers. If these mature firms then have relatively high debt-levels, which is in line with the Static Trade-Off Theory, these relatively high levered firms could have more extreme changes in their market capitalizations. In case of deflating asset prices, these firms would be deflated more heavily. However, this is just one theory, many other potential effects might be in play.

Potential avenues for future research could focus on improving different aspects of this paper. An example of an aspect that could be improved is the inclusion of firm specific news as an extra control variable. Another example could be improving the measure of ticker pronounceability or even coming up with a better measure altogether. Furthermore, future research might focus on testing the effects of stock tickers in different context. Alter and Oppenheimer (2006) test ticker pronounceability in the context of IPO returns. It might be interesting to see whether other ticker characteristics might come in to play here as well. Another interesting setting could be testing the flows of funds to publicly listed Real Estate Investment Trusts (REITs) or mutual funds. This can even be done using the framework of Durham and Santhanakrishnan (2016) that is also used in this paper.

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Appendix A: Output tables for the robustness checks

Table A1: Output table robustness check 5.3.1: Regression estimates of the relationship between ticker characteristics and trading volume, Size Quintiles are included instead of the market capitalization.

	(1)	(2)	(3)	(4)	(5)
Ticker Length	-0.0453*				-0.0392
	(0.0265)				(0.0271)
Ticker Word		0.0769**			0.0595
		(0.0390)			(0.0431)
Pronounceability			0.0323		0.0096
			(0.0320)		(0.0350)
Alphabetical 1%				-0.0557	-0.0621
				(0.1850)	(0.1823)
Alphabetical 5%				-0.1115	-0.1198
				(0.0946)	(0.0946)
Alphabetical 10%				0.0224	0.0355
				(0.0786)	(0.0797)
Alphabetical 20%				0.0112	0.0087
				(0.0569)	(0.0572)
Alphabetical 50%				0.0117	0.0130
				(0.0337)	(0.0338)
Percentage Afloat	0.0110***	0.0110***	0.0110***	0.0110***	0.0110***
	(0.0009)	(0.0009)	(0.0009)	(0.0009)	(0.0009)
LogSales	-0.0499***	-0.0471***	-0.0476**	-0.0478***	-0.0486***
	(0.0169)	(0.0168)	(0.0168)	(0.0169)	(0.0169)
LogDebt/Equity ratio	0.0100	0.0125	0.0126	0.0123	0.0103
	(0.0138)	(0.0136)	(0.0136)	(0.0136)	(0.0138)
LogMarket/Book ratio	0.0184	0.0138	0.0152	0.0151	0.0171
	(0.0223)	(0.0222)	(0.0222)	(0.0223)	(0.0225)
Constant	1.5267***	1.3246***	1.3311***	1.3433***	1.4734***
	(0.2081)	(0.1846)	(0.1846)	(0.1860)	(0.2100)
Industry controls	Yes	Yes	Yes	Yes	Yes
Size Quintiles	Yes	Yes	Yes	Yes	Yes
N	2017	2017	2017	2017	2017
F-statistic	20.26***	20.51***	20.36***	17.05***	15.45***
R^2	0.1865	0.1866	0.1854	0.1860	0.1886

Note. Superscripts *, ** and *** represent statistical significance at the 10%, 5% and 1% level respectively.

Table A2: Output table robustness check 5.3.2 (1/2): Regression estimates of the relationship between ticker characteristics and trading volume in which microcaps are excluded from the sample.

	(1)	(2)	(3)	(4)	(5)
Ticker Length	-0.0480*				-0.0427
	(0.0271)				(0.0276)
Ticker Word		0.0693*			0.0444
		(0.0390)			(0.0431)
Pronounceability			0.0391		0.0213
			(0.0322)		(0.0354)
Alphabetical 1%				-0.0531	-0.0572
				(0.1868)	(0.1839)
Alphabetical 5%				-0.1016	-0.1111
				(0.0958)	(0.0956)
Alphabetical 10%				0.0266	0.0383
				(0.0793)	(0.0804)
Alphabetical 20%				0.0217	0.0196
				(0.0574)	(0.0577)
Alphabetical 50%				-0.0092	-0.0084
				(0.0334)	(0.0336)
Percentage Afloat	0.0108***	0.0108***	0.0108***	0.0108***	0.0107***
	(0.0009)	(0.0009)	(0.0009)	(0.0009)	(0.0009)
LogMarketCap	-0.0144	-0.0131	-0.0116	-0.0098	-0.0139
	(0.0210)	(0.0209)	(0.0209)	(0.0210)	(0.0211)
LogSales	-0.0472**	-0.0437**	-0.0444**	-0.0451**	-0.0464**
	(0.0210)	(0.0203)	(0.0204)	(0.0203)	(0.0204)
LogDebt/Equity ratio	0.0143	0.0169	0.0172	0.0170	0.0147
	(0.0144)	(0.0141)	(0.0142)	(0.0141)	(0.0144)
LogMarket/Book ratio	0.0174	0.0134	0.0147	0.0134	0.0155
	(0.0237)	(0.0237)	(0.0237)	(0.0238)	(0.0239)
Constant	1.7434***	1.3585***	1.3527***	1.3607***	1.6984***
	(0.1791)	(0.1227)	(0.1233)	(0.1233)	(0.1805)
Industry controls	Yes	Yes	Yes	Yes	Yes
N	1917	1917	1917	1917	1917
F-statistic	21.99***	22.04***	22.02***	18.00***	16.09***
R^2	0.1831	0.1827	0.1820	0.1821	0.1850

Note. Superscripts *, ** and *** represent statistical significance at the 10%, 5% and 1% level respectively.

Table A3: Output table robustness check 5.3.2 (2/2): Regression estimates of the relationship between ticker characteristics and changes in market capitalizations in which microcaps are excluded from the sample.

	(1)	(2)	(3)	(4)	(5)
Ticker Length	-2.1733**				-2.9214***
	(0.8525)				(0.9029)
Ticker Word		-3.4859**			-4.1575**
		(1.6030)			(1.7994)
Pronounceability			-0.9668		-0.1855
			(1.3469)		(1.4831)
Alphabetical 1%				7.0886	7.0686
				(5.7755)	(5.8543)
Alphabetical 5%				-5.7005	-6.2349
				(4.9284)	(4.9798)
Alphabetical 10%				8.4375	8.7592
				(4.5162)	(4.6042)
Alphabetical 20%				-2.3488	-2.2762
				(2.0963)	(2.0693)
Alphabetical 50%				0.2836	0.3460
				(1.3512)	(1.3522)
LogSales	3.3277***	3.5553***	3.5394***	3.5219***	3.2514***
	(0.3708)	(0.3599)	(0.3606)	(0.3623)	(0.3715)
LogDebt/Equity	3.1688***	3.2304***	3.2430***	3.2758***	3.1357***
ratio	(0.5013)	(0.4989)	(0.5006)	(0.4999)	(0.5003)
LogMarket/Book	-8.6255***	-8.5333***	-8.6528***	-8.6094***	-8.4223***
ratio	(0.7308)	(0.7317)	(0.7332)	(0.7383)	(0.7335)
Constant	-18.3169***	-26.2932***	-26.5729***	-27.2925***	-14.6256***
	(5.0169)	(3.6638)	(3.7341)	(3.6734)	(5.1649)
Industry controls	Yes	Yes	Yes	Yes	Yes
N	1919	1919	1919	1919	1919
F-statistic	67.34***	67.87***	67.07***	53.52***	47.12***
R^2	0.4297	0.4296	0.4283	0.4307	0.4345

Note. Superscripts *, ** and *** represent statistical significance at the 10%, 5% and 1% level respectively.

Table A4: Regression estimates of the interaction effects of the alphabetical groups in combination with Size Quintiles on the change of the market capitalization. TC stands for the tested ticker characteristic which can be observed in the first row.

	Top 1%	Top 5%	Top10%	Top 20%	Top 50%
Top *X* %	13.4421*	4.6025	4.9334	2.3990	-0.2926
	(7.2684)	(4.0171)	(3.1902)	(2.4700)	(1.9543)
SQ2	7.1353***	6.9092***	7.1531***	6.9337***	6.6315***
	(1.7729)	(1.8069)	(1.8215)	(1.9363)	(2.4652)
SQ3	8.2804***	8.4290***	8.8530***	8.6602***	7.4941***
	(2.1060)	(2.1197)	(2.1889)	(2.2361)	(2.5558)
SQ4	9.2123***	9.3606***	9.3893***	10.1804***	9.3721***
	(2.6167)	(2.6124)	(2.6804)	(2.6984)	(3.0229)
SQ5	17.3646***	17.8879***	17.8061***	18.3456***	16.8943***
	(3.7335)	(3.7409)	(3.5377)	(3.6014)	(4.2068)
Top *X* % * SQ2	-0.2878	3.9836	1.6228	1.1033	1.3262
	(9.6342)	(6.5135)	(5.4373)	(3.6612)	(3.0135)
Top *X* % * SQ3	-1.8731	-1.1378	-2.2946	-0.6412	2.3169
	(10.0417)	(6.4694)	(5.4273)	(3.9301)	(3.0311)
Top *X* % * SQ4	-19.4814	-5.0433	-0.5438	-4.4035	0.1684
	(15.5109)	(6.6797)	(5.5443)	(4.3205)	(3.3297)
Top *X* % * SQ5	-37.5445***	-16.5160	-1.5637	-4.1362	1.6053
	(8.0131)	(10.7543)	(11.2060)	(6.4785)	(4.8024)
LogSales	5.6485***	5.6804***	5.7913***	5.7449***	5.8012***
	(0.6054)	(0.6023)	(0.6304)	(0.6103)	(0.6054)
LogDebt/Equity	2.5308***	2.5139***	2.5047***	2.5028***	2.4871***
ratio	(0.4972)	(0.4985)	(0.4982)	(0.4972)	(0.4968)
LogMarket/Book	-6.4532***	-6.3663***	-6.3159***	-6.3728***	-6.3238***
ratio	(0.8805)	(0.8770)	(0.8928)	(0.8795)	(0.8818)
Constant	-53.7939***	-54.0273***	-55.4689***	-54.8676***	-54.8456***
	(5.8322)	(5.8067)	(5.8965)	(5.9051)	(5.9225)
Industry controls	Yes	Yes	Yes	Yes	Yes
N	1919	1919	1919	1919	1919
F-statistic	Unobserved	43.21***	43.83***	43.89***	43.52***
R^2	0.4392	0.4394	0.4395	0.4387	0.4382

Note. Superscripts *, ** and *** represent statistical significance at the 10%, 5% and 1% level respectively.

Table A5: Regression estimates of the relationship between ticker characteristics and changes in market capitalizations using data from the Toronto Stock Exchange (TSX).

	(1)	(2)	(3)	(4)	(5)
Ticker Length	-9.1894***				-9.9947***
	(2.5770)				(2.7273)
Ticker Word		8.5216			8.0037
		(6.6785)			(6.6298)
Pronounceability			9.3571*		9.7896*
			(5.2407)		(5.3044)
Alphabetical 1%				-23.9605**	-18.6312*
				(9.7694)	(10.7375)
Alphabetical 5%				2.5804	-1.3766
				(9.7694)	(9.6008)
Alphabetical 10%				1.6927	4.4568
				(9.2255)	(9.4251)
Alphabetical 20%				-0.9195	0.1356
				(7.7775)	(7.6908)
Alphabetical 50%				-1.4631	-2.2181
				(4.9217)	(4.9315)
LogSales	-0.0003	-0.0002	-0.0001	-0.0001	-0.0002
	(0.0002)	(0.0002)	(0.0002)	(0.0002)	(0.0002)
LogDebt/Equity	9.7403**	10.5045***	12.7818***	10.4966***	12.2374***
ratio	(3.7985)	(0.0136)	(4.2781)	(3.7825)	(4.2987)
LogMarket/Book	-59.9440***	-62.8175***	-62.9220***	-62.3308***	-61.8577
ratio	(9.3124)	(9.2461)	(9.2618)	(9.1560)	(9.4862)
Constant	54.4561***	27.2413***	-3.2306	4.5360	28.5840***
	(8.6466)	(4.9531)	(8.2557)	(8.4555)	(11.2429)
Industry controls	Yes	Yes	Yes	Yes	Yes
Size Quintiles	Yes	Yes	Yes	Yes	Yes
N	521	521	521	2017	2017
F-statistic	19.14***	16.62***	17.36***	13.29***	13.28***
R^2	0.4836	0.4802	0.4822	0.4796	0.4912

Note. Superscripts *, ** and *** represent statistical significance at the 10%, 5% and 1% level respectively.